FOUR ESSAYS ON THE URBAN LABOUR MARKET IN INDIA

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ABSTRACT

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FOUR ESSAYS ON THE LABOUR MARKET IN URBAN INDIA

This thesis explores labour market processes in urban India. Investigating large and persistent differentials in urban unemployment rates across the Indian states, we find that regions with higher wage push or better amenities have higher unemployment rates, controlling for labour force composition. The differentials are maintained by rural-urban migration rather than by barriers to inter-state migration. Our investigation of wage determination yields evidence of imperfect competition in the labour market which is not simply 'institutional'. Indian firms pay efficiency wages which induce sufficient productivity gains to pay for themselves. After identifying the long and short run structural processes in the labour market, we consider recent aggregate trends in India's factory sector. There was negative employment growth in the 1980s even as output growth touched record levels. Our analysis suggests that this had less to do with wage growth, as proposed by the World Bank, and more to do with increasing work intensity, encouraged by wage incentives, improved infrastructure and increased competition. Considerable slack was inherited from the past, evidence of which flows from the wage and production function estimates. We find that increased labour utilization raises capacity utilization. This is important because Indian industry has chronically carried large excess capacity. A breakthrough in total factor productivity growth accompanied declining employment in the 1980s and has been interpreted as the reward of deregulation in this decade. Existing studies mismeasure productivity growth by neglecting labour utilization (hours) and assuming perfectly competitive product markets. We produce new estimates at the aggregate and industry levels. A natural ceiling to hours worked moderates bad news on the employment front and good news on the productivity front. Our analyses are expected to contribute to the evaluation of current and controversial policy changes in India.

Dedicated to my parents

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CHAPTER 1. INTRODUCTION
UNEMPLOYMENT, WAGES, EMPLOYMENT AND PRODUCTIVITY IN URBAN INDIA

This thesis explores aspects of the functioning of labour markets in urban India. Structure and competition claim particular interest. Motivated by the existence of remarkably large and persistent differentials in unemployment rates across the Indian states, we[1] study the long run equilibrium in a regional labour market. This provides a backdrop to the rest of the analysis since the Indian states appear to constitute separate labour markets, though, as we discover, there is considerable segmentation within each. There are the widely-recognized rural-urban and informal-formal sector dualisms, with the urban formal sector appearing to maintain uncompetitively high wages. The latter observation stimulates investigation of wage-determination in the 'formal' manufacturing (or factory) sector. Apart from being well-paid, factory jobs are regular and secure in an increasingly 'casual' economy. Therefore, negative growth in factory employment witnessed in the 1980s is a serious matter. While the concomitant breakthrough in total factor productivity growth has been celebrated as the reward of deregulation in this period, job losses in the factory sector have encouraged skepticism of the policy changes. In view of this, our attempt to explain employment and productivity behaviour in the 1980s is of topical interest. The data are a regional panel in the unemployment analysis and an industry-region panel for the rest of the work. So, we are able to allow for region-specific intercepts in the wage, employment and production functions. Careful attention is paid to econometric specification and method, and the estimators used are sensitive to errors in variables, heterogeneity of intercepts, endogeneity and, where possible, to the fact that the data panels have a short time dimension. In the rest of this chapter, we introduce the motivation of each of the analyses

[1] Merely as a convention, *we* is used throughout this thesis in place of *I*.

to follow.

There is enormous variation in unemployment rates across the Indian states. In 1972, unemployment by the daily status measure was 23% in Kerala and 4% in Uttar Pradesh and in 1987 this range was only marginally narrower, with Kerala having an unemployment rate of 22% and Uttar Pradesh, of 5%. There was similarly little convergence in usual status unemployment, which ranged between 11% and 2% in 1972 and 14% and 3% in 1987 in these same states[2]. In addition, the state structure of unemployment rates exhibited considerable rigidity over time. Rank correlations of quinquennial observations in the period 1972-87 lay between 0.70 and 0.88. These properties of the data may be a reflection of stiff barriers to mobility or, alternatively, of equilibrium. Which is in fact the case is the subject of **Chapter 2**. We attempt to identify the two structural relations that describe cross-region migration behaviour and within-region wage-setting behaviour respectively. Their interaction in the long run equilibrium implies a level of unemployment that both equates expected utilities across regions and reconciles the objectives of wage and price-setters. We estimate reduced form regional unemployment and wage equations that reflect this. By virtue of using both the usual and daily status measures of unemployment, the analysis is sensitive to the existence of substantial underemployment in India.

The persistence of regional differentials in unemployment rates begs the question of arbitrage or of why, given time, sufficient people do not move from high to low unemployment states. When looking at the level of unemployment in a given region, the natural question is why the unemployed are unable to undercut prevailing wage levels. While a significant negative impact of unemployment on wages in a region is identified in Chapter 2, the levels of unemployment in India suggest that wages are not market-clearing, at least not in every sector of the economy. This leads us to investigate, in **Chapter 3**, factors that inhibit market-clearing. The analysis is confined to the factory sector which is the registered manufacturing sector, consisting of firms with at least ten workers with power

[2] The usual status unemployment rate picks up unemployment that has endured for the greater part of the year whereas the daily status rate picks up underemployment in addition to this.

or at least twenty without. While this is only a small part of the urban economy, it is the largest provider of regular jobs outside the government service sector. Moreover, factory statistics are available by industry and region for nine years, 1979-87, whereas there are no other systematic wage data. An analysis of the factory wage data shows huge variations across industry and region and the distributions are very stable over the time period of our study. This further motivates consideration of non-competitive wage determination. We estimate a model that is consistent with both wage bargaining and the payment of efficiency wages and seek evidence of the influence of industry characteristics on wages. We also determine the extent to which the various included variables can explain the observed variation in wages along the dimensions of industry, state and time.

Having estimated the long run[3] and short run supply curves in Chapters 2 and 3, in **Chapter 4** we turn to an analysis of the demand side of the labour market. At this stage, we are less interested in sectoral structure and more interested in the time profile of employment. In the 1980s, in the factory sector, both productivity and wages accelerated and employment decelerated. A healthy supply of factory jobs takes on significance in India both because these are regular jobs[4] and because the expansion of manufacturing is expected to absorb the 'surplus labour' from the agricultural sector. We provide an analysis of the causes of the decline in factory employment and, in particular, take issue with an analysis of the World Bank (1989) that attributes it primarily to an acceleration in wages in the 1980s. We offer an alternative explanation that springs from the observation of rising days worked (and effort) per worker and takes account of both the longer-term dynamics of employment and the policy stimulus to competition in this decade.

Concomitant with the slackening of employment growth starting in the early 1980s was a surge in output growth in the factory sector and in the wider economy. Capital productivity,

[3] The long run is defined as a time span in which the labour force of a region is endogenous on account of migration.

[4] Casual workers, who constitute 12% of the urban work force, earn just more than a third of the daily factory wage and face income insecurity.

which had exhibited negative growth during the previous two decades ceased to decline. As a result, there was an acceleration in total factor productivity of apparently unprecedented magnitude in India. In **Chapter 5**, we estimate production functions and measure total factor productivity growth for the aggregate registered manufacturing sector and its constituent two-digit industry groups. In view of our analysis of the path of employment, particular attention is paid to estimating the marginal productivity of additional days worked per worker. Ours is the second set of estimates of growth in total factor productivity in Indian manufacturing in the 1980s. On account of methodological improvements relative to the existing analysis (Ahluwalia, 1991), it is expected to be the more reliable of the two. Productivity measurement takes on particular significance in view of recent changes in economic policy designed to release various constraints on activity in registered manufacturing. The reorientation began in the late 1970s, gained momentum in the 1980s and was consolidated into a new economic policy in 1991. There is as yet no analysis of post-1991 productivity but this is likely to become a fertile avenue of research.

Having obtained what we regard as robust estimates of the production function parameters, we are equipped to find out whether, *ceteris paribus*, wage increments pay for themselves by inducing higher productivity, that is, whether Indian firms pay efficiency wages. In Chapter 3, we seek evidence of imperfect competition in the labour market but do not have a way of distinguishing bargaining from efficiency wage outcomes. **Chapter 6** complements the analysis of wage determination in Chapter 3, using the production framework established in Chapter 5. In **Chapter 7**, we point out the limitations of the analyses and indicate some future directions for research. The main results from each chapter are recapitulated and placed in their broader context.

CHAPTER 2

INTERSTATE URBAN UNEMPLOYMENT RATE DIFFERENTIALS

1. INTRODUCTION

1.1. The Evidence

The geographic structure of unemployment

Unemployment rates vary dramatically across the regions of India. In 1987/88, the *daily status* unemployment rate (*URDS*) ranged between 22.4% in Kerala and 5.2% in Uttar Pradesh. The *usual status* rate (*URUS*) ranged between 14.1% and 3.4% in these same states (**Table 1**). Between the 1970s and the 1980s, some tendency towards convergence of unemployment rates across regions is evident. However it is small and the ranking of states by unemployment rates has not changed significantly[1]. The primary objective of this paper is to explain the persistent differentials in unemployment rates observed across the Indian states.

To our knowledge there is no study of *urban*[2] wage and unemployment rate differentials across regions in India or, indeed, any other less-industrialized country. Not unnaturally, in such countries, the dominant concern for economists and policy-makers is poverty. In high-income countries, unemployment is a positive correlate of poverty. Across Indian regions, however, the correlation between the two variables is negative and insignificant. In the absence of a well-developed social security system, the very poor cannot afford to be unemployed. The majority of the poor belong to families that engage primarily in agricultural activity where, at least for landowners, measures of open unemployment are not

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[1] Coefficients of variation are reported in **Table 1**. Rank correlations of the regional unemployment rate structure are in **Appendix Table A1**.

[2] Sundaram and Tendulkar (1988) analyze regional differences in poverty and rural unemployment in India.

Table 1
URBAN MALE UNEMPLOYMENT RATES
By daily (URDS) and usual (URUS) status

	(1)		(2)		(3)		(4)	
	1972/73		**1977/78**		**1983**		**1987/88**	
State	**URDS**	**URUS**	**URDS**	**URUS**	**URDS**	**URUS**	**URDS**	**URUS**
Andhra Pradesh	10.8	6.5	10.7	7.1	9.4	5.4	10.1	6.4
Assam	3.3	3.8	4.0	4.8	6.5	4.9	5.7	5.3
Bihar	7.6	5.2	8.0	6.1	6.8	5.6	7.9	6.4
Gujarat	6.5	2.9	6.8	3.9	7.7	5.1	7.1	4.7
Haryana	7.7	4.2	7.0	5.4	7.6	4.5	6.7	4.6
Karnataka	8.4	5.0	10.4	6.0	9.0	5.7	9.5	5.6
Kerala	23.0	11.2	25.0	16.2	22.7	11.9	22.4	14.1
Madhya Pradesh	4.1	4.0	5.9	4.3	5.8	3.4	6.0	4.3
Maharashtra	7.5	4.4	9.0	6.6	9.1	5.9	8.5	6.5
Orissa	5.8	5.2	8.9	6.5	8.5	5.4	8.6	7.1
Punjab	6.0	3.2	4.7	3.2	7.1	4.0	6.8	4.8
Rajasthan	5.1	2.2	5.5	3.7	5.5	4.2	7.2	4.7
Tamil Nadu	9.8	6.3	13.3	7.9	15.1	7.9	12.3	7.3
Uttar Pradesh	4.3	2.0	6.7	4.1	7.4	4.5	5.2	3.4
West Bengal	9.6	7.5	11.7	9.8	12.7	9.8	11.8	9.0
Chandigarh	N.A.	N.A.	2.9	2.2	8.8	8.2	10.1	10.3
Delhi	4.3	3.0	7.1	6.0	4.1	3.3	4.4	4.3
INDIA	7.7	4.9	9.4	6.5	9.2	5.9	8.8	6.1
Coefficient of variation(%)	58.0	46.6	56.1	50.8	46.9	38.4	45.5	33.7

Notes: Definitions of *URDS* and *URUS* are in the **Data Appendix**. N.A.=not available. *Source:*Sarvekshana, various issues.

very meaningful (Sen, 1975). In fact a common assumption in the developing country literature (eg., Harris and Todaro, 1970) is that there is *no* rural unemployment. However, even as the poor remain concentrated in the rural sector, accelerating urbanization across the developing world in the 1970s (Todaro, 1994) has stimulated a new concern about social problems in the urban sector. Prime amongst these is the growing number of unemployed people. For example, in 1987, 4.6 million people were unemployed in urban India by the usual status measure, and more by the daily status measure[3]. The general approach to this

[3] In the same year and by the same definition, 7.1 million were unemployed in the rural sector, where 74% of Indians live.

issue, led by Todaro, is to recommend policies directed at rural development. This is expected to stem the tide of job-seekers flowing from rural to urban regions and so, to ameliorate open urban unemployment. In this view, urban unemployment is associated with slums, crime and other forms of destitution. At least in India, a conflicting view is that unemployment is a *luxury* enjoyed by the better educated from well-off families (Blaug *et al*, 1969). The conflict is unresolved only because it is not clear who the unemployed are. We shall begin by setting out some descriptive statistics that go some way towards establishing this. Lack of interest in these statistics cannot be justified by skepticism regarding the concept of unemployment in India because the National Sample Survey (NSS) team have carefully devised an employment-unemployment survey that is sensitive to working conditions in rural and urban areas of the economy.

Unemployment by age, education and income group

Table 2 shows that the unemployment rate is significantly higher for young people, who

Table 2
Urban Male Unemployment Rates by Age-Group

Age Group	% of population	UR	LFPR
5-14	24.4	9.3	6.7
15-29	29.3	13.8	72.0
30-44	18.6	2.1	98.0
45-59	10.6	2.2	92.5
60+	5.3	2.2	47.8
Total	100	6.8	55.2

Table 3
Urban Male Unemployment Rates by Educational Category

Education group	% of populat ion	UR	LFPR
Illiterate	27.7	1.8	87.1
Primary	35.7	4.6	86.7
Middle	13.3	8.8	72.7
Secondary	15.9	8.8	70.7
Graduate+	7.0	7.4	86.4
Total	100.0	6.0	80.2

Notes: All figures are in percentages. UR=unemployment rates and LFPR=labour force participation rates. Both are weekly status measures. *Sources: Education data (refers to 1987):* Sarvekshana, Sept. 1990, Table 54.2. *Age data (simple average of 1977-87 data):* following issues of Sarvekshana. For 1977/8, from the July-Oct.1981 issue, Tables 4 & 6; for 1983, from the April 1988 issue, Table 24 and for 1987/8, from the Sept. 1990 issue, Table 42. The reported figures are averages of these data over the three years.

constitute more than 50% of the population. For those older than 30, there is little variation in unemployment rates by age group. This is consistent with high turnover amongst the young, as also with the idea that a large fraction of the unemployed consist of first-time job-seekers. From **Table 3**, it is clear that the incidence of unemployment is lowest amongst the illiterate population and that it peaks amongst those with middle to secondary level education, who comprise about 30% of the population. While graduate unemployment is very high, it is somewhat smaller than in this group, casting doubt on the Blaug hypothesis. The relation of unemployment rates to monthly per capita expenditure also broadly follows an inverted U-shape (**Table 4a**). **Table 4b** presents educational levels of the population by per capita expenditure. The proportions in columns 2 and 3 ('lower education') decline secularly and the proportions in columns 5 and 6 (higher education') rise continuosly with

Unemployment Rates and Educational Achievment by Expenditure Group

		Table 4a		Table 4b					
MPCE class	% of popul.	URUS (adjusted)	URDS	not literate	literate to primary	middle	secondary	graduate & above	all
<90	7.1	4.3	11.1	41.2	30.8	14.1	10.8	3.1	100
90-110	7.2	3.6	11.2	38.6	35.7	15.2	9.2	1.2	100
110-135	11.8	5.0	10.6	31.2	36.7	18.3	11.8	1.9	100
135-160	11.8	6.1	11.1	22.9	36.6	20.6	16.4	3.5	100
160-185	10.3	5.9	11.0	20.2	34.8	21.3	18.8	5.0	100
185-215	10.1	6.6	10.1	14.8	31.7	21.0	25.3	7.0	100
215-255	10.5	5.5	8.6	13.3	29.2	21.1	26.9	9.6	100
255-310	9.2	6.1	9.0	10.3	24.1	19.0	32.7	13.7	100
310-385	7.9	5.6	8.4	9.4	20.6	17.1	36.6	16.3	100
385-520	6.9	5.2	6.7	8.1	19.2	14.3	35.4	23.0	100
520-700	3.4	2.5	3.8	5.9	11.5	12.7	38.8	31.1	100
700+	3.0	4.0	5.3	4.2	9.9	9.5	38.3	38.1	100
All	100.0	5.7	10.4	18.1	28.3	18.0	24.6	10.9	100

Notes: All figures are in percentages. Data pertain to 1987. MPCE is monthly per capita expenditure in Rs., popul is population, URUS is usual status and URDS is the daily status unemployment rate, defined in the **Data Appendix**. The unemployment rates refer to all persons and the education rates to males of 15+ years only. *Source:* Sarvekshana, 1990.

p.c. expenditure. We use this information to investigate the luxury unemployment hypothesis. **Tables 2** and **3** indicate a negative correlation between unemployment and labour force participation rates, possibly reflecting discouraged worker effects[4].

[4] We report data for *urban males* since it is the unemployment of this group that is the subject of the empirical analysis to follow. However the data for urban *females* and *rural* males exhibit similar patterns. For example, unemployment rates for youth in the rural sector are twice as high as for older age groups.

1.2. Existing Work and Contributions of the Present Study

The chief and possibly only contribution to the analytics of inter-sectoral differences in unemployment is the Harris-Todaro model (Harris and Todaro, 1970). This has been widely applied to understanding the consequences of rural-urban migration in developing countries (see Todaro, 1976) and has provoked investigations of the determinants of such flows (eg., Banerjee, 1983). The empirical literature falls neatly into two mutually exlusive categories. One set, comprising primarily U.S. studies, are in the Harris-Todaro mould[5]. The central tenet is a positive equilibrium relationship of wage and unemployment rates across sectors. Proposing to contend this view, more recent work based on cross-sectional data for many countries has claimed that the unemployment-wage relationship across space is negative (Blanchflower and Oswald, 1992). We take an approach that resolves the debate by positing that the regional labour market equilibrium rests on two distinct relations, one negative and one positive[6]. The rubric of the model was developed by Jackman, Layard and Savouri (1991) in proposing a theoretical framework for evaluation of mismatch in OECD countries. It is *modified* and *extended*, and, as far as is known to the author, *estimated* for the first time. The modifications and extensions introduced are specified in **Section 2**. We emphasize how our extended model represents a natural evolution of the literature on migration and unemployment in less industrialized countries. Given the importance of the Harris-Todaro model in development economics, this work purports to fill a significant gap in the literature on labour markets in developing economies. Arguably the most significant contribution of

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[5] These include Hall (1970, 1972), Adams (1985), Browne (1978), Reza (1978) and Bucci (1993). Marston (1985) is more exploratory. In his study of unemployment differentials between U.S. metropolitan areas, he allows for a disequilibrium component to the unemployment rate and *estimates* the speed of adjustment. However, like the other studies, he is concerned with one structural relation rather than with a labour market equilibrium.

[6] There is no correlation between unemployment and wages in the Indian data, which is consistent with both the positive and negatively sloped curves having shifted over the period. The high unemployment states of Kerala, West Bengal and Tamil Nadu are not all associated with low wages, and moreover, do not strike one as chronically depressed regions of the country. They are not all associated with high wages either, although there may be some case for suggesting that each of them is associated with positive differential amenities.

this work is that the existence and persistence of differentials in urban unemployment rates between the Indian states has not been recognized, let alone analyzed.

1.3. The Approach

Interpretation of regional unemployment differentials

Consider a spatial equilibrium disturbed by an adverse demand shock specific to one region. If wages do not adjust instantaneously, this will lead to an increase in unemployment in that region which, in turn, is expected to cause wages to adjust downwards when next negotiated. At the same time, some of the unemployed may migrate out of the region or, attracted by lower wages, capital may move in[7]. Due to some combination of these processes, the effects of the shock are made transient over a period that is long enough for barriers to migration to be overcome and for wage contracts to expire. The numbers in employment and in the labour force may change but the wage and unemployment rates adjust back to their initial equilibrium level. This is why, barring fixed compositional differences between regions (eg., education, age), *persistent* differentials in unemployment rates may strike the economist as puzzling.

It appears that, during 1972-87 in India, the three equilibrating forces were not doing their job. Consideration of capital mobility is beyond the scope of this work. In this chapter, we investigate the other two forces, namely, the flexibility of wages to unemployment and migration behaviour. In a world with more than one sector, the latter is the central issue. Even if wages do not adjust to market-clearing levels, given time why don't enough people move from high to low unemployment sectors? Long run differentials in unemployment rates can appeal to at least two possibilities. The first is costs, or financial, social and psychological *barriers* to migration, there being no legal barriers to movement between Indian regions. Limited mobility combined with low demand constitutes the early wisdom as regards high unemployment in a region (eg., Robinson, 1937). However, surveying a

[7] Policy intervention that raises local employment is also potentially effective in returning the regional economy to equilibrium.

variety of studies, Papola (1992, p.41) concludes that labour mobility in response to employment opportunities, both rural to urban and across regions, has not been found wanting. Thus, while costs will affect the *speed* of adjustment to an equilibrium, it seems unlikely that they can account for a geographical pattern of unemployment that has hardly changed over a period as long as fifteen years. The alternative possibility is that job prospects and living conditions are better in the regions with relatively high unemployment rates. At least as important as wage increments in India are secure jobs. These are mostly in the organized sector which, in turn, is concentrated in urban areas. In addition, there are wide differences in health and educational facilities between the Indian states. So, even in the absence of barriers to movement, it is conceivable that people may choose not to migrate. In this case, the unemployment differentials constitute an *equilibrium* in tandem with wage and amenity differentials. A third possibility arises in the context of an industrializing country. Suppose that there is a rural-urban equilibrium within states but disequilibrium between states. The disequilibrium generates urban-urban migration from high to low unemployment states. This disturbs the internal equilibrium, thereby stimulating rural-urban flows in the high unemployment states and urban-rural flows in the low unemployment states. As a result, the inter-state unemployment differential is maintained. In other words, there is a *perpetual disequilibrium*[8]. The underlying assumption here is that barriers to rural-urban movements are smaller and the corresponding speed of adjustment greater as compared with urban-urban inter-state movement. We conceive of the rural-urban movements as intra-state, though the existence of inter-state rural-urban flows does not upset the structure of the model. Having discounted the hypothesis that costs or barriers explain everything, we investigate the other two hypotheses.

To fix the notion of an equilibrium differential, we may think of the unemployment rate in a region at any time as comprising three elements: an economy-wide average for period t (θ_t), an equilibrium differential for each region (λ_s) and a disequilibrium component (ξ_{st}). In general, the effects of a shock persist into the next period, or $\xi_{st}=\rho\xi_{st-1} + e_{st}$, where $(1-\rho)$

[8] Perpetuity follows from assuming that the number of potential migrants in the rural sector is infinite.

is the fraction of the disequilibrium that is eliminated in one period. One approach, taken by Marston (1985), is to estimate ρ. If it is small enough, then the observed regional differentials reflect equilibrium differentials, λ_s, which suggest that people are generally happy where they are. The approach taken here starts with a description of migration behaviour, from which an inter-area equilibrium condition is derived. If this is well-determined, then the observed unemployment differences are predominantly equilibrium differences.

The regional labour market equilibrium

First consider the equilibrium hypothesis. To investigate whether this can explain the observed differentials, a migration equilibrium condition is fitted to the data. This condition implies that, controlling for regional amenities, regions with relatively high wages have relatively high unemployment rates. Alongside this *between-region* relation, we estimate a *within-region* relation of unemployment and wages that is described by a wage setting function. This reflects the fact that, in any given state, there is a tendency for high unemployment relative to the natural rate to exert downward pressure on the wage. The wage-setting function determines where, along the migration equilibrium curve, a certain region will lie. Some of the variables that shift this function, namely wage-push factors or non-wage opportunities open to workers, are region-specific. For example, states with stronger unions or conditions more favourable to self-employment may be expected to have higher wage and unemployment rates compared to others. Reduced forms of the two structural equations are also estimated. Apart from wage push and amenity variables, aspects of the quality and composition of the labour force, such as caste and age, figure in the analysis.

2. A MODEL OF THE REGIONAL LABOUR MARKET EQUILIBRIUM

In **Section 2.1**, we consider the short run and in **Sections 2.2** and **2.3**, the long run. The basic structure of the two-sector model was contributed by Jackman, Layard and Savouri *or JLS* (1991). We have modified the wage setting function by allowing the regional wage to depend upon regional productivity. This introduces a positive reduced-form dependence of the unemployment rate in a region on its productivity, reflecting the idea that high productivity regions attract more in-migration. This may strike some as counter-intuitive. However, it is consistent with a long run that is long enough to permit migration and yet not so long as to have eradicated productivity differentials between states. Productivity levels between industries and regions are typically more disparate in developing as compared with developed countries and this is probably particularly true in a country the size of India[9]. Like Harris-Todaro, JLS assume risk-neutrality in setting up their migration equilibrium condition and they specify the probability of employment as (1-U), where U is the unemployment rate. Since workers are likely to be risk-averse and the employment probability may be a more complicated function of unemployment, our model relaxes these assumptions. Further, we make a clear distinction between costs and amenities whereas, somewhat misleadingly, JLS model costs as if they were negative amenities. Possibly our most significant contribution is that we extend the simple two-sector model of JLS to incorporate as a third sector, the rural economy, which interacts closely with the urban economy in low-income countries.

2.1. THE SHORT RUN MODEL

Neither the question that motivates this work nor the available data favour estimation of a short run model. Nevertheless, it is useful to set it out in order to arrive logically at the formulation of the long run model. The short run is defined as a period in which the labour force in a region is exogenously fixed. Each region constitutes an independent labour market (**Figure 1**). Wages and employment in the regional economy are simultaneously determined by the wage setting function and the employment function[10]. Given the labour force, the unemployment rate is determined. Wage setting is the subject of **Chapter 3** and employment determination of **Chapter 4**, so their treatment here is somewhat cursory.

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[9] See Section 2.2 of **Chapter 5**.

[10] Just as the wage setting function is the imperfect competition surrogate of the labour supply curve, so, under imperfect competition, there is an employment function rather than a labour demand curve.

2.1.1. The Wage-Setting Function

In a perfectly competitive labour market, the wage is set at a level that balances demand and supply. If there are disequilibria marked by the appearance of unemployment, then the wage adjusts downwards. In fact, we observe levels and durations of unemployment that cannot be deemed frictional. So, it appears that the labour market is imperfectly competitive. Evidence for India (see **Chapter 3**) and other countries (Layard, Nickell and Jackman 1991, chapter 4) suggests that firm-specific variables like productivity and size interact with external market variables like unemployment in determining the wage. A simple wage setting function that encompasses these possibilities (refer Section 3.1, **Chapter 3**) is

$$W_s = h[\pi_s, Z_s, (1 - U_s), X_1] \qquad (1)$$

where s is a region subscript, W is real earnings per worker[11], U is the unemployment rate, π is productivity, Z is a vector of *wage push* factors or factors that shift the wage function in W-U space, and X_1 are aggregate variables that may include productivity, unemployment and wages. The partial derivatives of h satisfy $h_1, h_2, h_3 > 0$.

The impact of unemployment on wages

The unemployment elasticity, h_3, is of most interest in this chapter. Each of the theoretical wage models encompassed by (1) implies a negative impact of unemployment on wages. The *efficiency wage model* posits that the existence of a high rate of unemployment helps the firm to recruit, retain and motivate workers. To this extent, the incentive for the firm to offer high wages for these purposes is diminished (eg., on motivation, see Shapiro and Stiglitz, 1984)[12]. The case of *dynamic monopsony* (Mortenson, 1970) can be subsumed under the recruitment model of efficiency wages, whereby the firm that wants to raise its employment raises its wage to attract a well-qualified pool of applicants. In a framework

[11] The deflator is a regional consumer price index that is discussed in setting out the empirical model. Denote it as P_s^c.

[12] However high wages have an edge over high unemployment in performing the *recruitment* function. This is because, in a situation of excess labour supply, where quantity is forthcoming, quality might still be difficult to separate out. See Stiglitz (1987) for a discussion of the dependence of quality on price.

in which wages are set by a *bargain* between firms and workers (Nickell and Kong, 1992), high unemployment outside makes it easier for the firm to initiate turnover and makes it harder for the unemployed to find alternative employment. The consequent fear of job-loss weakens workers' bargaining power. This is true whether or not workers are organized into unions[13]. As pointed out by Blanchflower and Oswald (1992), *Marxist* accounts of the reserve army of the unemployed are consistent with this argument. Once compositional effects are controlled for, a pure *market* effect of excess supply on price is also consistent with the hypothesis of unemployment depressing wages. Evidence of the negative impact of unemployment on wages has been found in time series (e.g. Christofides and Oswald, 1989) and panel data studies (e.g. Nickell and Wadhwani, 1991) of other countries. Blanchflower and Oswald (1994) report cross-sectional evidence for a wide selection of countries.

2.1.2. The Employment Function

Consider a simple production function for aggregate value added (Y),

$$Y = \Sigma_s Y_s, \text{ where } Y_s = \phi_s K^{\beta}_s N^{\alpha}_s \tag{2}$$

Again, s is a region subscript; K=capital stock, N=employment and ϕ=a shift factor. Setting $\partial Y/\partial N_s = W_s/P_s$, the average product wage in the region, gives the marginal product condition,

$$W_s(P_s^c/P_s) = \alpha(Y_s/N_s) \tag{3}$$

where P_s is the average product price and P_s^c and W_s have been defined as the consumer price and the consumer wage respectively. Allowing for imperfectly competitive product markets makes little difference to this formulation (see Section 3, **Chapter 4**).

2.1.3. The Short Run Equilibrium

For a given labour force, equations (1) and (3) are solved to give

[13] An alternative view, in which bargaining seems implicit, has been proposed in the Indian context. This is that a rise in unemployment increases the [family] *responsibility* of the employed and therefore, their wage demands (Dasgupta, 1976).

$U_s = f^1[(Z_s, \pi_s, X_1]$ (4a)

$W_s = f^2[Z_s, \pi_s, X_1]$ (4b)

Thus, in the short run equilibrium, the regional unemployment rate depends positively on wage pressure and productivity. The vector of wage pressure variables, Z, includes the price wedge, (P_s/P_s^c), which is the ratio of the product to the consumption price index. The regional wage is determined by the same set of independent variables. In addition, economy wide conditions (X_1) potentially impact on both variables.

2.2. THE LONG RUN MODEL

In the *long run*, the regions in an economy are interdependent and the labour force in any region is endogenous on account of inter-regional migration[14]. Regions with low labour demand need not be regions with high unemployment because the unemployed have the option to leave the region. Therefore, consideration of migration behaviour is crucial to understanding unemployment rate differentials in the long run. We shall first develop the basic theory for a two-sector model and then generalize to a three sector case.

2.2.1. The Migration Equilibrium Condition

2.2.1.1. Migration in a two-sector model

Workers are expected to migrate in the direction of high wages and other benefits (or *amenities*) as long as there is a reasonable chance of finding a job. We suppose that this chance grows more slim as the unemployment rate in the region rises. The implied *migration function* is

$M_s/L_s = g[(W_s/W), (N_s/L_s)/(N/L), (A_s/A)]$ (5)

where s is a region-subscript, M is net migration into region s, L is the labour force, W is the wage, N is employment, A is amenities and variables with no region subscript are

[14] Natural increase in the labour force of a region may also depend upon its economic conditions. However, we do not model this possibility here.

macro-variables. The first derivative of g with respect to each of its arguments is positive. Of course, the unemployment rate U is (1-N/L)[15]. Amenities are all region-specific factors other than wage and unemployment rates that impact on worker utility. There appears to be some confusion over what is an amenity as opposed to a migration barrier. The following example illustrates this. A *migration barrier* which has claimed considerable attention in the UK is the high cost of rental accommodation in the low-unemployment region[16]. On the other hand, an *amenity* in many US studies (e.g., Hall 1972, Marston 1985) is the area covered by parks in the high-unemployment region. In fact, the first is a disamenity associated with the destination region and the second is an amenity associated with the source region. We shall distinguish barriers from amenities by the following rule. Amenities are specific to particular regions, while migration barriers or *costs* are specific to ordered pairs of regions (and are not antisymmetric). Thus, the cost of moving from A to B need not be the negative of the cost of moving from B to A, which makes costs difficult to model. On the other hand, if region B has a positive amenity relative to A, then the gain in moving from A to B equals the loss in moving back, from B to A. Consequently, this feature may, equivalently, be written as a positive amenity of B or a negative amenity of A. Migration is commonly modelled as a function of the expected wage, with the probability of finding employment assumed to be the employment rate (eg., Harris and Todaro 1970; Jackman, Layard and Savouri 1991). The expected wage characterization assumes risk neutrality, but workers are very likely to be risk averse. In particular, given equal expected wages in two regions, they are likely to prefer a region with low wages and low unemployment to a region with high wages and high unemployment. This is especially true in a country like India where per capita income is low and there are no social security provisions. Furthermore, the employment probability faced by a migrant may be a more complicated function of the employment rate. For these reasons, we do not restrict the arguments of (5).

[15] No doubt, some migration is driven by non-economic motives. However, there is no reason to suppose that this is systematically uni-directional.

[16] For instance, McCormick uses the term 'barrier' in this context in his comments on Bover, Muellbauer and Murphy (1989).

Migration continues until expected utility is equal across regions. Therefore the long run spatial equilibrium is defined as a state characterized by zero net flows. Setting $(M/L)_s=0$ gives a locus of equilibria that slopes upwards in the wage-unemployment rate space ($f_1>0$):

$$U_s = f[W_s/W,\ A_s/A,\ U] \tag{6}$$

The first derivatives of f are all positive. This curve is called the *migration equilibrium condition* (or *MEC*). Differentially positive wages and amenities attract a larger volume of wait unemployment.

2.2.1.2. Migration in three-sector models

We shall now incorporate into the migration model the fact that the urban sector in any Indian state is hinged to a substantial rural sector. The three sectors are then the rural and urban sectors of a state and the agglomeration of other urban sectors.

Global equilibrium

Suppose that the urban sectors of states are in equilibrium with one another and also with their rural sectors, or that there is a global equilibrium. Then there are two *independent* migration equilibrium conditions, the first of which we have already encountered:

$$U_s = f[W_s/W,\ A_s/A,\ U] \tag{6}$$

$$U_s = f[W_s/W_{rs},\ A_s/A_{rs},\ U_{rs}] \tag{7}$$

where the subscripts, *s* and *rs* refer to the urban and rural sectors of a state, *s,* and unsubscripted variables are averages for the urban sectors of all other states. All first derivatives of f are positive. Equation (6) describes the inter-state equilibrium and (7) describes the intra-state equilibrium.

The Harris-Todaro model

Harris and Todaro (1970) proposed a restricted version of the MEC in (7), written as

$$W_s(1-U_s) = W_{rs} \tag{8}$$

which says that the urban unemployment rate, U_s, depends on the log wage-differential with a unit elasticity. Its restrictiveness arises from (a) neglect of non-economic influences (amenities) on utility, and the assumptions of (b) risk neutrality, (c) no rural unemployment (U_{rs}=0), and (d) exogeneity of the wage. The last is, arguably, the most serious assumption as it results in the MEC being regarded as a complete one-equation model. In fact, unemployment rates are simultaneously determined with wages and (8) leaves the regional labour market equilibrium indeterminate because, given two unknowns, we require two equations.

Perpetual disequilibrium

As mentioned in **Section 1.3**, an alternative possibility is that the urban sector of a state is in equilibrium with its rural sector but not with other urban sectors. In response to the inter-urban disequilibrium, migrants flow from high to low unemployment states. This disturbs the within-state equilibrium, resulting in rural-urban migrants replenishing the urban stock. If the internal equilibrium is always quickly restored then the external disequilibrium will be maintained indefinitely. Of course, the same process operates in the low unemployment state, except that the flows are reversed. This story provides an alternative to migration barriers in explaining why the urban sectors of states have been slow to converge. It is predicated on the speed of rural-urban adjustment exceeding that of inter-state adjustment and on there being an effectively infinite pool of rural labour. Perpetual disequilibrium generates a somewhat different 'equilibrium condition'. The presumption of lesser friction in internal as compared with external movements implies that the *volume* of migration *out of* the urban sector of a state (M_{out}) will be exactly matched by that *into* it (M_{in}). Employing the rubric of the basic equilibrium model, we may write

$$M_{out} = L_s\ g[(W/W_s,\ U/U_s,\ A/A_s] \qquad (9)$$

$$M_{in} = L_{rs}\ g[(W_s/W_{rs},\ U_s/U_{rs},\ A_s/A_{rs}] \qquad (10)$$

where M is the number of migrants and the rest of the notation is as in (6)-(7). Equation (9) describes inter-state urban-urban migration and (10) describes within-state rural-urban migration. By our hypothesis, M_{out}=M_{in}. Solving this condition gives

$$U_s/U = f[W_s/W,\ W_{rs}/W,\ A_s/A,\ A_{rs}/A,\ U_{rs}/U,\ L_{rs}/L_s] \tag{11}$$

Now the urban unemployment rate in a state (U_s) depends on its wage and amenity attributes (W_s, A_s), corresponding conditions in other urban sectors (U, W, A), *and* those in its rural sector (U_{rs}, W_{rs}, A_{rs}). In addition, it depends on the relative *size* of the urban and rural sectors (L_{rs}/L_s). In **Section 4**, we investigate (11) as well as (6) and (7).

While the perpetual disequilibrium hypothesis posits a rural-urban equilibrium, the net rural-urban migration rate is *not* expected to be zero (see **Section 2.3.1** as well). Rather, in a high unemployment state, the hypothesis is that the rural sector is *systematically* feeding the urban sector with migrants. However, one may speak of a rural-urban *equilibrium* because any (inter-state) out-migration from the urban sector is immediately met by in-migration from the rural sector and so an equation of expected incomes between the sectors is maintained. Hence (7) may be expected to hold along with (11). However, if the data satisfy (11) then they will not satisfy *both* (6) and (7).

2.2.2. The Long Run Labour Market Equilibrium

The equilibrium of migration flows may be thought of as a *long run supply curve* for labour. The point on this curve at which a particular region lies is determined by the position of the wage-setting function, the *short run supply curve* for the region. Thus the long run equilibrium for a certain region is described by the intersection of these two curves (see **Figure 2**).

2.2.2.1. Equilibrium in the two-sector model

The two structural forms are the wage-setting equation in (1) and the inter-state migration equilibrium condition (or MEC) in (6). The implied reduced forms are

$$U_s = f^1\ [Z_s,\ \pi_s,\ A_s,\ U,\ W,\ A,\ X_1] \tag{12a}$$

$$W_s = f^2\ [Z_s,\ \pi_s,\ A_s,\ U,\ W,\ A,\ X_1] \tag{12b}$$

where subscript s refers to the urban sector of a state and unsubscripted variables refer to averages for all other urban sectors. Thus a region will maintain a positive unemployment rate differential if it is associated with *relatively* high levels of wage-push (Z), productivity (π) and amenities (A). The equilibrium wage rate is also positively related to each of wage push and productivity, but a positive amenity differential implies a negative compensating differential in the regional wage.

Figures 1 and 2: Equilibrium in a Regional Labour Market

The Short Run **The Long Run**

2.2.2.2. Equilibrium in the three-sector models

Global equilibrium

When the urban sector of a state is in internal *and* external equilibrium, then its unemployment rate is described by the intersection of (1) with *either* (6) or (7). The reduced forms are given by equations (12) *or*

$$U_s = f^1 [Z_s, \pi_s, A_s, U_{rs}, W_{rs}, A_{rs}, X_1] \quad (13a)$$

$$W_s = f^2 [Z_s, \pi_s, A_s, U_{rs}, W_{rs}, A_{rs}, X_1] \quad (13b)$$

where subscripts s and rs refer to the urban and rural sectors of a state, respectively.

Perpetual disequilibrium

In this case, the long run equilibrium is given by solving (1) and (11) simultaneously:

$$U_s = f^1\ [Z_s, \pi_s, A_s, U_{rs}, W_{rs}, A_{rs}, L_{rs}/L, U, W, A, X_1] \tag{14a}$$

$$W_s = f^2\ [Z_s, \pi_s, A_s, U_{rs}, W_{rs}, A_{rs}, L_{rs}/L, U, W, A, X_1] \tag{14b}$$

So, the equilibrium configuration for the urban region reflects its interactions with other states and with its rural sector. Which of (12)-(14) is estimated in **Section 5** will be determined by the results of estimating the structural model. If the data support a global equilibrium, we shall estimate (12) and (13) but if they favour a perpetual disequilibrium, we shall estimate (14).

2.3. Reflections On The Long-Run Equilibrium

2.3.1. The notion of equilibrium in the migration condition

The migration equilibrium condition has been defined as the locus of unemployment-wage combinations that preclude arbitrage opportunities and therefore imply zero net migration. When such an equilibrium is disturbed by a demand shock in some region, migration is stimulated. If migration were sufficiently rapid, we would observe an equilibrium because the disequilibrium wage and unemployment rate levels would not last long enough to be picked up in our data. There would then be no contradiction between observing persistent non-zero migration and supposing that wage and unemployment levels are in equilibrium. Indeed, the existence of non-zero migration flows would strengthen our belief in the idea that migration is acting to annul arbitrage opportunities, thereby moving the system to its equilibrium. How far we typically are from equilibrium would depend upon the frequency and size of demand shocks and the speed of migration-induced adjustment. The speed of adjustment depends upon the severity of economic and social barriers. It might be worth pointing out that achieving equilibrium typically only requires that a small part of the labour force be mobile. The fact that some workers face prohibitive costs merely determines *who* moves. Well-determined estimates of the MEC would imply that we are close enough that we cannot reject the hypothesis of an equilibrium.

2.3.2. The notion of equilibrium in a regional labour market

The juxtaposition of the two supply functions determines a rate of unemployment that tempers 'infeasible' wage claims *and* sets a limit to queuing for jobs. In both cases, unemployment brings the system into equilibrium. We speak of the unemployment rate that emerges as an equilibrium rate. Notions of desirability or of market clearing are not necessarily attached to this usage. In the first case the equilibrium unemployment rate is better known as the non-accelerating inflation rate of unemployment and is characterized by stabilization of the inflation rate, corresponding to a given degree of wage pressure. In the second case, equilibrium is of spatial labour markets and is characterized by the equation of expected utilities between regions. Note that the second case encompasses or implies the first, so that in a long run spatial setting, the two aspects of equilibrium will coincide at E in **Figure 2**. Observed unemployment in any given region deviates from its equilibrium value as a result of region-specific demand and/or supply shocks. Thus there may well be a disequilibrium component to the actual unemployment rate. In view of the data at hand and the question that it raises, we investigate whether the equilibrium *component* is large enough to be identified.

2.3.3. Invariance to demand

An interesting property of the long run model is that the equilibrium wage and unemployment rates are independent of demand conditions. The two unknowns, W and U (or [1-N/L]), are obtained from the *two supply equations*, the MEC and the wage-setting equation and demand only serves to allocate the labour force (L) between regions. Together with the constraint that the sum of the labour forces of the different regions equals the total labour force, or $\sum_s L_s = L$, these three equations determine the three variables, W, N and L. A region with relatively high labour demand grows faster. It has a higher level of employment (N) but, on account of in-migration, it also experiences relatively rapid growth of its labour force (L). Hence, in the long run, its unemployment rate (1-N/L) is independent of demand.

3. THE EMPIRICAL MODEL

3.1. Data and Estimation issues

The estimates are based on a panel of quinquennial data for the 14 major states of India for the four years in 1972-87. There are no reliable time series data on unemployment. Details are in the **Data Appendix.** We were not dissuaded by the smallness of the sample because the question motivating this analysis has not been explored at all. However, our results should be regarded as somewhat tentative.

Since the four cross-sections span a period of fifteen years, we investigate the temporal stability of the estimated coefficients. The structural model is computed with each regressor interacted with each of four year-dummies, one for each year. We find that in estimates of the migration equilibrium condition for 1972, the coefficient on the wage is significantly smaller than in other years. However, the coefficients on the other variables are quite remarkably similar in the four years. In view of these results, we estimate the model on a *reduced sample* consisting of the later three cross sections. Results of estimation on the *full sample* are also reported.

The structural model (equations 1 and 7) is linearized by taking logarithms of all variables other than the unemployment rate (U), which provides a better fit than its logarithm. *Compositional variables (C)* are included to control for relevant aspects of heterogeneity in the labour force. All aggregate variables, X, are captured by *time dummies*. Given that the data are a panel, standard procedure would require that we include *state dummies* in the model so as to isolate the *within-group* variation in the data. However, in our context, this commands some discussion. In the migration equilibrium condition (MEC) amenities are, by definition, features inherent to regions and so they will be highly collinear with the state fixed effects. So as to identify the features that matter, we prefer to specify a set of amenities and exclude the fixed effects. In the wage setting equation, there is a stronger case for controlling comprehensively for state fixed effects. Unlike the MEC which is really a cross-sectional relation, the wage function encapsulates a time-varying process within a region. To separate out the pure state-time variation from the state and time specific effects, we should ideally have both state and time dummies in the model. However, with just four cross-sections, including state dummies would wipe out most of the variation in the data[17]. Although the inclusion of compositional variables may be expected to make up for the omission of state dummies to a fair extent, we nevertheless estimate a version of the wage equation that includes state dummies.

The *estimated structural model* may be written as:

$$U_{st} = \theta_0 + \theta_t + \beta_1 w_{st} + \beta_2 a_{st} + \beta_3 r_{st} + \beta_4(lf_{rst}-lf_{st}) + \beta_5 c_{st} + v_{st} \tag{15}$$

$$w_{st} = \kappa_0 + \kappa_t + \kappa_s + \alpha_1 U_{st} + \alpha_2 \pi_{st} + \alpha_3 z_{st} + \alpha_4 c_{st} + \varepsilon_{st} \tag{16}$$

Lowercase letters denote natural logs, subscript *s* denotes the urban sector of a state while subscript *rs* denotes its rural sector, t is a year subscript, θ_0, κ_0 are the common intercepts, θ_t, κ_t are vectors of year dummies, κ_s are state fixed effects, U=unemployment rate, w=wage, a=amenities, r=rural variables, lf=labour force, z=wage pressure variables, π=productivity, c=compositional variables and v_{st} and ε_{st} are error terms that are expected to be stochastic. Equation (15) is based on (11) in the theoretical model and derives from the perpetual disequilibrium hypothesis. The year dummies pick up the aggregate variables, U, W and A. The vector of rural variables, r, includes U_{rs} and W_{rs}. Unfortunately, there are no data on A_{rs}. Since (15) incorporates variables pertaining to intra and inter-state migration, we shall refer to it as the *portmanteau equation.* The condition for an inter-state equilibrium (eq.6) can be arrived at by imposing on (15) the restrictions that β_3, β_4=0. The rural-urban migration equilibrium condition (eq.7) is also encompassed by (15) and corresponds to θ_t, β_4=0. As we do not have access to data on rural amenities (A_{rs}) and they cannot be assumed to be equal across states, we also impose β_2=0, which gives a modified Harris-Todaro model.

Equations (15) and (16) are estimated by two-stage least squares (2SLS), with U and w treated as endogenous. The instrument set derives from the reduced form equations, estimated by OLS and reported in **Table 14**. Basmann's F test for instrument validity

[17] An ANOVA of the unemployment rate shows that *state* accounts for 95.5% of the variation in URDS and 86.4% of the variation in URUS. The residual is allocated between *time* and the error.

(Basmann, 1960) is reported for each equation. The null hypothesis is that the coefficient on each variable that is in the instrument set but excluded from the equation under consideration is in fact zero. If the null hypothesis is rejected then some of the instruments are correlated with the equation error and so are not valid.

3.2. Identification

Changes in wage pressure and productivity make it possible to identify the migration equilibrium equation, while changes in amenities and rural variables trace out the wage-setting function. Are these exclusion restrictions valid? The migration function only features variables that impact directly on worker utility, so once the wage is in, there is no case for productivity and wage pressure variables to enter the MEC. It may be argued that amenities should enter the structural wage equation as compensating differentials. However, we suppose that any fallback opportunities of workers that figure in a wage bargain and comparison wages that might influence their unobservable efficiency are within-state variables (see **Chapter 3**). Then both the actual and the alternative wages are subject to the same state-specific compensating differential and so this factor cancels out. Therefore we do not include amenities in the structural wage equation.

3.3. The Variables

Definitions and sources are in the **Data Appendix**. Here we discuss the rationale behind each variable and any peculiarities or problems that arise.

3.3.1. The Endogenous Variables

The unemployment rate (U_{st} ; URDS or URUS)

The unemployment statistics refer to urban males[18]. Aggregate unemployment rates for males and females in urban and rural areas are set out in **Table A2** by the three alternative measures of unemployment provided by the NSS; defined in the **Data Appendix**. In this analysis, we use the *usual status* (*URUS*) rate, which counts *persons* unemployed for the

[18] Since determinants of women's unemployment are quite different, the data on men and women are not combined.

most part of the year and the *daily status (URDS)* unemployment rate which is a *personday* rate that, in addition, picks up underemployment. This is important in an economy in which sustained open unemployment is not an option for a large part of the population and there is only a thin line between underemployment and unemployment.

The wage (W_{st}; wage)

The wage is defined as real annual earnings per worker in the registered manufacturing (or *factory*) sector. To take care of cross-sectional differences in the cost of living, we use a price index for the average urban consumer in each state relative to the nation as a whole, ie India=100 (Minhas *et al*, 1987). So as to also take account of time variation in prices within regions, we combine this with a price index for each state relative to a base year, ie 1970=100 (Minhas *et al*, 1990) to get the wage *deflator*.

Table 5
Average Earnings in Different Sub-Sectors of Manufacturing India
Rupees p.a. in 1974-75 [% differential]

Registered manufacturing (or factories)		*Unregistered manufacturing*	
Census	**Sample**	**Urban**	**Rural**
4288 [100]	1913 [44.6]	1551 [36.2]	822 [19.2]

Sources: The registered sector data are from the Annual Survey of Industries (CSO, 1974/75) and unregistered sector data are from the 29th round of the National Sample Survey.

Since the factory sector constitutes only a small fraction of the urban economy, defining wages with reference to it is restrictive. A better measure might be GDP per worker for the urban sector of the state, but we do not have the required data. We have chosen the factory wage for the following reasons. First, a majority of factory jobs (9 in 10) is regular and hours per day are relatively standardized. Since unemployment in a country like India largely takes the form of irregular and low-paid employment, regular employment is the best approximation to what is usually understood as employment. Second, migrants are most likely to be motivated by the prospect of relatively *well-paid and protected* employment, especially if they are risk averse. Regular factory employees have job security. **Table 5** shows that they are relatively well-paid; Mazumdar (1984) documents survey evidence of their longer job tenures. Third, this is the only wage series that is consistently available in published statistics. Finally, if in fact the average wage across all urban occupations is the more relevant statistic, then the factory wage might be defended as the kingpin of the urban wage structure, driving all other wage rates in the regional economy[19]. The average urban wage can then be written as a weighted sum of wages in *regular* [r], *casual* [c] and *self-employment* [s][20]:

$$W_{urban} = \nu_r W_r + \nu_c W_c + (1-\nu_r-\nu_c)W_s \tag{17a}$$

where the weights, ν, denote the fractions of the urban work force in the three activities. We do not have state data on W_c and W_s. In line with the kingpin tenet, we assume that these are constant fractions, ρ_c, ρ_s, of the regular wage, W_r. Then,

$$W_{urban} = \nu_r W_r + \nu_c \rho_c W_r + (1-\nu_r-\nu_c)\rho_s W_r \tag{17b}$$

So, in addition to W_r, we include, as regressors, the proportion of the urban work force in regular and casual employment (ν_r or *regular*, ν_c or *casual*). This is considerably less restrictive than simply defining W_{urban} as W_r. Regular employees are largely in the factory and public sectors, so we proxy the regular wage with the factory wage.

3.3.2. Wage Push Variables (Z_{st} and Z_s)

These are variables that shift the structural wage function drawn in the wage-employment rate space. *Labour productivity (productivity$_{st}$)* is expected to raise wages, given unemployment. The impact of *strikes* could go either way. Both variables refer to the factory sector, like the wage. For discussion of the regional productivity deflator (P_{st}) and indices of union power that were tried as alternatives, see the **Data Appendix**.

3.3.3. Wage Push *and* Amenity Variables (W and A)

The following set of variables may be interpreted as wage pressure or amenity variables and

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[19] Data on unorganized and organized sector wages in Kerala is consistent with this idea (Kannan, 1992). His analysis hints that non-factory wages drive factory wages, rather than the other way around. The following empirical strategy is robust to this possibility.

[20] The NSS classifies the urban work force into these three categories.

so they enter directly into *both* the migration equilibrium condition and the wage-setting relation. A high probability of a public sector job (*public sector*) is considered a positive amenity because it offers perquisites, including more holidays, subsidized *canteens*, shorter working hours and, most of all, greater job security. In fact, Lal (1988) ascribes urban unemployment in India entirely to queuing for public sector jobs. It is also designated as a wage pressure variable on the grounds that public sector workers face a lower risk of job loss, and know that their managers have a relatively flexible budget. *Left-wing* is a dummy created to allow for fixed effects peculiar to West Bengal and Kerala, the two states in our sample that are unique in having a history of left wing government (or, equivalently, class-conscious populations). It is expected to attract a positive coefficient in both equations. Since the left wing state governments are particularly sympathetic to the industrial working class, it is expected that they attract net in-migration of workers[21]. This is the amenity effect. Based on a variety of indices, Mohanakumar (1989) ranks Kerala and West Bengal as the most dispute-prone states. The greater protection and militancy of workers in these states suggest that they will lay claim to higher wages, other things being equal. This is the wage-push effect. In addition, including this dummy serves to control for *outlier effects*. Kerala's unemployment rate is clearly well away from the rest of the scatter, and the data for West Bengal also have outlying tendencies (**Table 1**).

A metropolitan dummy *(metropolis$_s$)* is created to distinguish the states with three of India's four big cities[22]- Bombay, Madras and Calcutta- from the others. It is expected to pick up any effects of industrial and urban *agglomeration*. In the light of higher land prices and more squalor and crime, *metropolis* may be regarded as a *negative amenity*. However, there

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[21] The case for attracting workers from rural or urban areas of other states is clear. However, it may be argued that rural to urban migration *within* Kerala and West Bengal will not be any greater on account of their political character. This depends on whether the left-wing governments in these states have created a differential advantage in the status of urban as opposed to rural workers. One reason to believe that this might be the case is that it is harder for any government, left wing or other, to afford effective protection to rural workers because, being 'remote' and largely unregistered, they are on a legal periphery.

[22] The fourth is Delhi. Until the early 1990s, Delhi was a union territory rather than a state and some of our data sources do not include it in the statistical breakdown of the economy by major states. Therefore it is excluded from the sample.

is evidence that rural workers tend to move to big cities, leapfrogging urban centres closer to their homes (eg., DeHaan and Rogaly 1993, Papola 1992: p.20). If we take revealed preferences seriously, then *metropolis* is a *positive amenity.* This can be reasoned in any of three ways. One is that metropolises have superior *social infrastructure* such as better health and educational facilities, relevant for the children of migrants. A second is that the *diversity* of job opportunities in metropolises reduces the risk of prolonged unemployment. This effect is expected to operate even though unemployment appears directly in the model since the unemployment rate does not reflect the dynamics of the labour market. For instance, risk aversion implies that people would prefer to be unemployed for one month in twelve as against one year in twelve and diversity makes the former more likely in a metropolis than in a small town, at *given* unemployment rates. Finally, *information* flows are better in metropolises. There is a historical pattern of migration into metropolises, which has stimulated contining migration on account of established kinship links. When they first arrive in the city, villagers often stay with friends and relatives from their birthplace (eg., Mazumdar 1984, Caldwell 1969). This offers some security in the venture of rural to urban migration, and thereby reduces barriers. The metropolitan dummy is potentially not just an amenity but also a *wage push* variable. The presumption is that worker organization is both easier and more effective in a metropolis than in a smaller urban centre. The metropolises have large universities in which political feeling is bred; they are state capitals that feature the range of political parties; and they afford individual workers greater anonymity than a small town in which employer-worker relations are more likely to be multi-faceted. These features make it more probable that workers will exercise wage push. Further, the effectiveness of their claims is bettered if economies of agglomeration result in greater surpluses from production.

3.3.4. Amenities (A_{st} and A_s)

The following variables enter the migration equilibrium condition but not the wage-setting function. As they are relevant to inter-state migration, they figure in both (6) and (11). Large *casual* and *construction* sectors are positive amenities if ease of entry into these sectors encourages *greater* in-migration. It is recognized that there is no general rule as to what jobs migrants target, and what they settle for but we are guided by the observation that most urban construction is performed by 'gangs' of rural migrants. In the absence of data on the wages of casual workers, *casual* is included in the model in any case (refer *wage* above). We define the infrastructural development of a region (*infrastructure*) as a further amenity. In addition to indices of the spread of power supply, roads, schools, etc., the available measure includes rural infrastructure such as irrigation. Thus, to the extent that urban unemployment in a state is attributable to in-migration from the rural sector, the *gap* in amenities between the two sectors is relevant but is not reflected in the statistic used. Therefore this variable is only relevant to *inter-state* migration.

3.3.5. Rural variables (R_{rst} or R_{rs})

These are determinants of expected incomes in the rural sector and they appear in the MEC in the naive Harris-Todaro model as well as in our three-sector model. According to the simple Harris-Todaro model, for given expected urban opportunities, the lower are rural incomes, the greater is rural-urban migration. It is inherently difficult to find an aggregative measure of rural incomes, given that agricultural labourers receive non-cash payments to varying extents. Rao (1972) and others have argued that the agricultural wage data in India are unreliable. Moreover, in view of increasing non-agricultural rural employment (Unni, 1986), wages in agriculture are only a part of the rural average. In the **Data Appendix**, we set out the alternative measures that are experimented with. To avoid confusion, Tables shall refer to the chosen measure as *the rural wage*, no matter which it is. The deflator is a state-specific rural price index derived in a manner similar to the deflator for the urban wage (see *wage* above).

Greater *rural unemployment* is expected to result in greater migration into urban areas, *ceteris paribus*. The Harris-Todaro model sets rural unemployment to zero on the basis that people can always eke out a living on the land. However, land distribution in India is highly skewed and as a result there exists a rural labour market and it does not appear to clear (**Table 15**). The rural unemployment rate is obtained from the NSS surveys that use the same criteria as for the urban rates (see *unemployment* above). To augment this measure, we also include the proportion of landless labourers in the agricultural labour force (*landless*) and the *rural population density*. There is a growing population of landless agricultural labourers who suffer greater unemployment and earn lower incomes than other rural workers (eg., CMIE, 1988). So, their migration propensities are likely to be especially high[23]. This is confirmed by Rosenzweig (1980). Finally, if the pressure of labour on the land is relatively high in the rural sector (*rural density*), we may expect greater out-migration. The *rural to urban labour force ratio* ($labour\ force_{(R/U)st}$) figures only under the disequilibrium hypothesis (eq.11). Both population and the labour force participation rate refer to the above-5 population[24].

3.3.6. Compositional variables (C_{st} or C_s)

Differences in labour force composition across states are quite significant. Some of the measurable attributes are considered now. We use two education variables, the proportion of urban males that is literate (*literacy*) and the proportion who have secondary or graduate-and-above qualifications (*higher education*). As it is quite undisputed that human capital is paid for in wages, both variables are expected to have a positive sign in the wage equation. Also, see **Table 6**.

Table 6
Returns to Education: Daily wages rates of regular employees in manufacturing

Not literate	*Literate to middle*	*Secondary*	*Graduate and above*	*All*
20.9	25.1	38.7	60.6	29.8

Source: Sarvekshana 1990, Table 79. Data are in Rs. and refer to urban males (15-59 years) in 1987/88.

The data (**Table 3**) show that the more educated have higher rates of unemployment, whether the comparison is between literate and illiterate groups (7.3% vs. 1.8% in 1987) or between more and less educated groups (8.03% vs. 4.85%, in the same year). Thus a positive sign is expected on these variables in the migration equilibrium condition as well.

[23] Based on a mammoth survey of migrants in Ghana, Caldwell (1969) reports that the main reasons for adult household members remaining in the rural area was family responsibility and *possession of a farm*. Neither the wage nor the unemployment rate in the rural sector captures these factors.

[24] **Table 2** shows that participation rate for 5-15 year olds is about 7% and for people more than 60 years old, it is 48%. So, the above-5 population may be a more relevant base in India than the 15-59 population.

Data on unemployment rates by age group show that the 15-29 year old group (*youth*) experiences by far the highest unemployment rate among the urban population (**Table 2**). Thus the proportion of the male population of each state in this age bracket is expected to gain a positive sign in the migration equilibrium relation when the unemployment rate is the dependent variable[25]. A negative sign is expected in the wage equation on the well-established grounds that wages are an increasing function of age (Mincer, 1974). The proportion of 'scheduled castes and tribes' (SC/ST) in the urban population of the state (*caste*) is entered to allow for the possibility that there is either negative or positive discrimination vis a vis either or both of wages or employment prospects for this group. *Caste* is also entered in interaction with poverty incidence in order to investigate the hypothesis that the impact of caste on unemployment is only because members of the SC/ST group are poor and so face employment and migration constraints that are peculiar to them. Causality is usually expected to run from unemployment to *poverty*. However, under a more 'structural' interpretation, it may run the other way. Regions with a higher incidence of poverty may have lower unemployment rates because the poor can least afford to be unemployed. Poverty then behaves like a *negative benefit rate*. It is expected to enter both structural equations with a negative sign.

Cyclical demand (Δy_{st})

Different states may be at different points of the business cycle in the survey years. To account for this, we have included the growth rate of state net domestic product. It is expected to take a negative sign in the MEC. If wages are procyclical then Δy will acquire a positive sign in the wage equation. Were the cycle synchronized across states, it would be captured by the time dummies in the model.

[25] It may also be argued that age enters the structural migration condition because it determines the likely duration of wage employment, if it is obtained, and therefore the benefit from it (eg., Knight, 1972). Similarly, education may be expected to encourage migration by raising aspirations (Peil, 1971). This may be rationalized in terms of information costs.

4. THE STRUCTURAL FORM ESTIMATES

Both equations are estimated on the *reduced sample* (1977-87) and the *full sample* (1972-87) and with both the *daily status* (*URDS*) and the *usual status* unemployment rates (*URDS*). The migration equilibrium condition (MEC) has three incarnations. Two arise under the equilibrium hypothesis, one each for the inter-state and the intra-state equilibria. The third arises under the disequilibrium hypothesis, when internal *and* external variables influence long run labour market conditions in the urban sector of any state. The unemployment and wage rates are treated as endogenous and instruments are given by the exclusion restrictions. In no case does Basmann's test for overidentifying restrictions reject their validity. All reported standard errors are corrected for heteroskedasticity, of which there was evidence. The main result is that two distinct unemployment-wage relations are identified, one positive and one negative. This is subject to some qualifications, which are discussed.

4.1. The Migration Equilibrium Condition

Refer to **Table 7**, where we employ the reduced sample and the dependent variable is *URDS*. Column 1 reports estimates of the particular equilibrium condition (M_{out}=M_{in}) that arises under the hypothesis of a perpetual disequilibrium (eq.11). Column 2 presents the condition for a migration equilibrium (M/L=0) within states (rural-urban) and column 3, the same between states (inter-urban). We first consider the implications of columns 1-3 for the equilibrium properties of the data and then move on to consider, all at once, the specific variables of interest in the three equations.

4.1.1. Have we identified a migration equilibrium?

Investigating perpetual disequilibrium*: *the portmanteau equation

Consider column 1, an estimate of eq.(11). There is a significant positive relation between unemployment and wages in the urban sector and the amenities take the expected signs. The ratio of the rural to the urban labour force is also significant. Significance of rural unemployment *and* the time dummies suggests that both rural-urban and inter-state

Table 7
THE MIGRATION EQUILIBRIUM CONDITION
2SLS estimates based on the *reduced* sample
Dependent variable=daily status unemployment rate(%)

	Three-sector model		Two-sector models
	(1)	(2)	(3)
Variable/ Variant:	**portmanteau**	**intra-state**	**inter-state**
wage	2.48 (2.3)	1.28 (2.4)	0.69 (0.3)
Wage Push & Amenity			
left wing	3.68 (7.9)		4.90 (5.2)
metropolis	(-, n.s.)		
public sector	0.19 (2.9)		0.23 (1.0)
Amenity			
construction labour	6.00 (4.5)		3.97 (2.4)
casual labour	2.43 (3.7)		
regular workers	-4.83 (3.6)		-1.93 (0.9)
infrastructure	(+, n.s.)		
Rural variables			
rural wage	(-, n.s.)	-0.11 (0.4)	
rural unemployment	0.17 (4.8)	0.43 (5.9)	
landless labour	2.46 (3.1)	0.69 (2.1)	
R/U labour force	0.63 (2.9)		
Composition			
literacy rate	6.75 (7.9)		6.74 (2.9)
youth (15-29 yrs)	(-, n.s.)		
caste	-1.54 (2.9)		-0.44 (0.6)
Δln (NDP)	-7.61 (3.6)		-10.6 (3.1)
Wald(time dummies)	45.5/2 (0.0)	n.a.	39.5/2 (0.0)
Adj.R_2 [N]	0.95 [42]	0.79 [42]	0.90 [42]
Root MSE	0.010	0.014	0.015
F-statistic	79.07 (0.0)	15.6 (0.0)	29.3 (0.0)
Basmann's F	0.73 (0.40)	0.56 (0.65)	0.78 (0.32)

Note: The sample mean of the dependent variable, URDS, is 9.48% and its standard deviation is 4.55.

migration contribute to shaping labour market outcomes in the urban sector[26]. These results support the hypothesis of perpetual disequilibrium and argue against the hypothesis

[26] The time dummies proxy the aggregate variables relevant to inter-state migration, namely U, W and A.

of a global equilibrium (**Section 2.2.1.2**). If there were a global equilibrium, identifiable by either (6) or (7), then estimates of (11) would produce an insignificant coefficient on the rural-urban labour force ratio. Further, the existence of an inter-urban equilibrium would imply the insignificance of the rural variables in (11) once aggregate variables are held constant by the inclusion of time dummies.

Rural-urban equilibrium: the Harris-Todaro equation

We now investigate the intra-state equilibrium described by equation (7). By the argument in **Section 2.2.1.2**, this is what maintains the disequilibrium between urban regions. Column 2 sets out a log-linearized Harris-Todaro equation released of the risk-neutrality assumption and, more generally, of unit restrictions on the coefficients. This model is devoid of non-economic migration drivers. However, in the absence of data on rural amentities, this naive model is preferred to an alternative that includes only urban amenities[27]. The results point to a well-determined equilibrium. The positive relation of urban unemployment and wages is significant, and steeper than in the portmanteau equation. The rates of rural unemployment and 'landlessness' are both significant. Agricultural productivity, a proxy for the rural wage, has the expected sign but is insignificant. This may be on account of these data being particularly noisy (see **Section 3.3.5**). The unit coefficient restrictions of the original Harris-Todaro model are not upheld by the data.

Inter-state equilibrium

Although the evidence is consistent with perpetual disequilibrium (eq.11), for completeness we estimate the model that derives from positing an inter-state equilibrium (eq.6). Column 3 is obtained by dropping the rural variables (U_{rs}, W_{rs} and also labour force$_{(R/U)rst}$) in column 1. As the urban wage is no longer significant, we cannot accept the null hypothesis of equilibrium. Disequilibrium causes the persistence of non-zero migration. Thus, estimation of (6) implies omission of the migration rate, $(M/L)_{st}$. Although we do not have migration

[27] We might have retained the urban amenities and compositional variables if it were the case that the rural sectors of all Indian states are very similar, for then these omitted rural variables could have been picked up by an equation constant. But this is not the case.

data, it follows from the intuition underlying (5) that corr(U_{st}, M/L_{st})<0 and corr(w_{st}, M/L_{st})>0, so that the wage coefficient is biased towards zero. The index of *infrastructure* was insignificant in the portmanteau equation but becomes significant once the rural variables are dropped. So, it counts as an amenity in inter-state migration but is obscured in the presence of rural-urban migration, which is unsurprising because it is an index of rural and urban infrastructure (see **Section 3.3.4**).

Conclusion

The alternative structural forms describing migration behaviour are summarized in **Table 8**. On balance, we favour the hypothesis of perpetual disequilibrium as a description of the processes at work and conclude that while an inter-state equilibrium does not seem to obtain, the data are consistent with a rural-urban equilibrium. Suppose inter-urban disequilibria are due to barriers to migration rather than to our favoured explanation of countervailing rural-urban flows. Then, the rural-urban equilibrium in any state would be undisturbed by what happens outside it and the equilibrium condition would be one of zero net migration between rural and urban areas. Therefore, the aggregate variables and the rural-urban labour force ratio would be insignificant in column 1, which is not what we observe.

Table 8
Stylized Forms of the Alternative Long Run Supply Curves

Variables	**portmanteau**	**inter-state**	**intra-state**
Urban wage (W_{st})	yes*	yes	yes*
Urban amenities (A_{st})	yes*	yes*	no
Aggregate variables (time dummies$_t$)	yes*	yes*	no
Rural variables (U_{rst} and W_{rst})	yes*	no	yes*
Rural-urban labour force ratio (labour force$_{(R/U)st}$)	yes*	no	no

Notes: *yes* indicates that the variables are included and an asterisk indicates that they are significant.

4.1.2. Variables that shape the long run supply curve

We now look more closely at the preferred equation in col.1 of **Table 7**. Though this describes a perpetual disequilibrium, we shall henceforth refer to it as the migration equilibrium condition or MEC since it does derive from equality of a certain pair of migration flows (**Section 2.2.1.2**). A positive *wage* differential of 10% is associated with a positive unemployment rate differential of 0.25 percentage points or 2.6%[28], the residual variation in unemployment being largely explained by regional amenities and the structure and attributes of the regional labour force.

Amenities that are significant have the expected signs. States with *left wing* governments and a concentration of *public sector* capital attract greater in-migration than others. These are the only clear amenity effects. Further candidates are the proportion of *construction and casual workers* in the urban work force. While these may be amenities signifying ease of entry to migrants, they may alternatively be compositional variables marking out the fact that such workers are prone to spells of unemployment between contracts. Or, by (17), they may be interpreted as components of the urban wage. In any case, it is clear that the migration condition has different intercepts for different work force categories and the signs on these are intuitive. For instance, the more *regular* workers in the work force, the less underemployment there will be. *Metropolis* and *infrastructure* are insignificant.

Other than, possibly, construction and casual, the only significant compositional effects flow from caste and literacy. States with a higher fraction designated as 'lower' *castes* have lower unemployment. This can be interpreted as a reflection of lower reservation wages in this group[29]. Survey evidence (Mehta, 1988) indicates that this group earns below-average wages, works long hours, and constitutes a major fraction of the urban poor. An interaction term between low-caste and *poverty* incidence was included and it appeared as positive but insignificant. States with more literate populations are associated with higher unemployment. The two states at the top of the unemployment ranking, Kerala and West Bengal, have two of the most literate populations. However, *literacy* is significant even though a dummy for

[28] Recall that the unemployment rates are not logged but the wage and other variables are. The sample mean of the unemployment rate (URDS) is 9.8% (reported in the Tables).

[29] The mobile are choosers. If 'low caste' people are relatively immobile on account of poverty or inadequately developed 'contacts', then changes in local demand conditions will impact relatively strongly on their wages (price adjustment). The more mobile will migrate out of the region (quantity adjustment). See Topel (1986) for a generalization of this idea.

these states (left-wing) is included. It may be seen as reinforcing a queueing notion of unemployment with the literate being more choosy. Alternatively, if the literacy rate is highly correlated with the provision of educational facilities, then it may be interpreted as an amenity on the grounds that migrants plan for the education of their children. *Age*, *poverty* and *higher education* are insignificant. Finally, states with rapidly *growing NDP* (Δy) have lower unemployment rates. This variable reflects the fact that different states are at different points of the business cycle in any year.

The state of the rural labour market has a significant impact on the conditions of urban workers. The *rural unemployment rate* is highly significant and *landless* has an independent well-determined effect. *Rural population density* has a positive sign but it is not well determined. This may be because of the positive association of land-productivity and population density in rural areas, which implies that crowding does not necessarily lower average incomes for the rural population. No measure of the *rural wage* is significant in column 1, but in column 2, agricultural labour productivity borders on significance and has the expected negative sign. Alternative measures of the wage are even less well-determined. Finally, states with a higher *rural-urban labour force ratio* ($LF_{R/U}$) have significantly more urban unemployment.

4.1.3. Some variants of the MEC

(i) The *daily status unemployment rate (URDS)* used so far is the broader measure, including underemployment in addition to the longer-term unemployment picked up by the *usual status rate (URUS)*. However, state differentials in URUS have the properties of persistence and slow convergence depicted by URDS (**Table 1**). **Table 9** presents estimates of (11) using URUS, along with the analogous URDS equation (cols. 4 & 3). The equilibrium relation between unemployment and the *wage* is steady against this variation, the implied elasticity being 0.29 as compared with 0.26[30]. Other differences between the two equations are discussed in **Section 5**. *(ii)* Investigation of the MEC on single cross sections revealed

[30] The sample mean of URUS is 5.9% and mean URDS is 9.5%.

Table 9
MAIN RESULTS: THE STRUCTURAL EQUATIONS ON THE *REDUCED* SAMPLE
The wage equation and the migration equilibrium condition: 2SLS estimates

	(1)	(2)	(3)	(4)
Dependent variable	**wage**	**wage**	**URDS**	**URUS**
wage			2.48 (2.3)	1.71 (2.2)
URUS		-4.70 (4.6)		
URDS	-2.50 (5.7)			
Wage Push				
productivity	0.47 (5.2)	0.52 (5.9)		
strikes	-0.014 (0.6)	-0.027 (1.0)		
Wage Push & Amenity				
left wing	0.35 (5.3)	0.40 (4.5)	3.68 (7.9)	2.46 (6.3)
metropolis	0.16 (3.6)	0.18 (3.6)	(-, n.s.)	(-, n.s.)
public sector	0.003 (0.2)	0.01 (0.6)	0.19 (2.9)	0.29 (5.1)
Amenity				
construction labour			6.00 (4.5)	1.88 (2.1)
casual labour			2.43 (3.7)	(+, n.s.)
regular workers			-4.83 (3.6)	-1.04 (1.1)
infrastructure			(+, n.s.)	(+, n.s.)
Rural variables				
rural wage			(-, n.s.)	(-, n.s.)
rural unemployment			0.17 (4.8)	0.19 (3.1)
landless labour			2.46 (3.1)	1.29 (2.7)
R/U labour force			0.63 (2.9)	0.56 (3.4)
Composition				
literacy rate	(+, n.s.)	(+, n.s.)	6.75 (7.9)	1.85 (2.0)
higher education	0.18 (1.2)	(+, n.s.)		
youth (15-29 years)	-1.90 (7.2)	-2.16 (8.1)	(-, n.s.)	(-, n.s.)
caste	(+, n.s.)	(+, n.s.)	-1.54 (2.9)	-0.63 (2.6)
Δln (NDP)	0.82 (2.8)	0.83 (2.9)	-7.61 (3.6)	-4.12 (2.4)
Wald(time dummies)	20.4/2 (0.0)	16.1/2 (0.0)	45.5/2 (0.0)	22.1/2 (0.0)
Adj.R_2 [N]	0.85 [42]	0.83 [42]	0.95 [42]	0.90 [42]
Root MSE	0.108	0.114	0.010	0.009
F statistic	30.17 (0.0)	21.31 (0.0)	79.07 (0.0)	37.7 (0.0)
Basmann's F	0.87 (0.52)	0.57 (0.64)	0.73 (0.40)	0.48 (0.62)
Dep. variable mean (s.d.)	3.58 (0.27)	3.58 (0.27)	9.48 (4.55)	5.91 (2.57)

Notes: The reduced sample=14 states X 3 years, R/U is rural/urban, URDS=daily status and URUS=usual status unemployment rate. Unemployment rates are in proportions in col.1 & 2 and in percentages in col.3 & 4.

Table 10
THE STRUCTURAL EQUATIONS ON THE *FULL* SAMPLE
The wage equation and the migration equilibrium condition: 2SLS estimates

	Daily status unemployment (URDS)		Usual status unemployment (URUS)	
	(1)	(2)	(3)	(4)
Variant:	**migration condition**	**wage-setting**	**migration condition**	**wage-setting**
wage	0.98 (0.7)		1.28 (2.3)	
URUS				-0.052 (8.6)
URDS		-2.80 (9.0)		
Wage Push				
productivity		0.45 (6.5)		0.52 (6.3)
strikes		-0.020 (0.7)		-0.031 (1.0)
Wage Push & Amenity				
left wing	3.52 (4.1)	0.34 (7.5)	2.50 (8.2)	0.39 (5.8)
metropolis		0.13 (4.0)		0.16 (4.0)
public sector	0.29 (2.6)	0.001 (0.1)	0.31 (7.2)	0.017 (0.9)
Amenity				
construction labour	4.78 (3.6)		1.98 (3.4)	
casual labour	1.19 (1.8)			
regular workers	-5.49 (3.2)		-1.22 (1.7)	
infrastructure				
Rural variables				
rural wage				
rural unemployment	0.25 (3.6)		0.17 (3.4)	
landless labour	2.22 (3.0)		1.56 (5.7)	
R/U labour force	0.72 (1.7)		0.58 (3.1)	
Composition				
literacy rate	5.49 (3.7)		1.88 (2.1)	(+, n.s.)
higher education		0.12 (1.2)		0.18 (1.5)
youth (15-29 yrs)		-1.82 (9.5)		-2.16 (12.1)
caste	-2.13 (2.7)		-0.53 (2.0)	(+, n.s.)
Δln (NDP)	-3.52 (1.9)	0.48 (1.7)	-2.13 (1.2)	0.58 (2.0)
Wald(time dummies)	9.5/3 (0.0)	21.0/2 (0.0)	25.7/3 (0.0)	
Adj.R_2 [N]	0.92 [56]	0.85 [56]	0.90 [56]	0.83 [56]
Root MSE	0.013	0.100	0.009	0.113
F statistic	65.0 (0.0)	32.4 (0.0)	41.0 (0.0)	25.1 (0.0)
Basmann's F	0.76 (0.37)	0.87 (0.52)	0.49 (0.62)	0.55 (0.65)
Dependent variable mean (s.d.)	9.48 (4.55)	3.58 (0.27)	5.91 (2.57)	3.58 (0.27)

Note: The *full sample* has 14 states observed over the 4 years, 1972, 1977, 1983 and 1987.

Table 11
VARIANTS OF THE MIGRATION EQUILIBRIUM CONDITION
2SLS estimates based on the *reduced* sample
Dependent variable=daily status unemployment rate

	(1)	(2)	(3)
Variable/ Variant:	**original portmanteau model**	**replace γ_t with aggregate variables**	**Dependent variable= wage**
wage	2.48 (2.3)	2.48 (2.3)	
URDS			6.70 (2.1)
Wage Push & Amenity			
left wing	3.68 (7.9)	3.68 (7.9)	-0.20 (1.4)
metropolis	(-, n.s.)	(-, n.s.)	
public sector	0.19 (2.9)	0.19 (2.9)	-0.008 (0.3)
Amenity			
construction labour	6.00 (4.5)	6.00 (4.5)	-0.87 (4.1)
casual labour	2.43 (3.7)	2.43 (3.7)	-0.020 (0.1)
regular workers	-4.83 (3.6)	-4.83 (3.6)	1.15 (5.6)
infrastructure	(+, n.s.)	(+, n.s.)	
Rural variables			
rural wage	(-, n.s.)	(-, n.s.)	
rural UR	0.17 (4.8)	0.17 (4.8)	-0.014 (1.8)
landless labour	2.46 (3.1)	2.46 (3.1)	-0.37 (3.1)
R/U labour force	0.63 (2.9)	0.63 (2.9)	0.13 (2.7)
Composition			
literacy rate	6.75 (7.9)	6.75 (7.9)	-0.51 (2.1)
higher education			
youth (15-29 yrs)	(-, n.s.)	(-, n.s.)	
low caste	-1.54 (2.9)	-1.54 (2.9)	0.25 (2.2)
Δln (NDP)	-7.61 (3.6)	-7.61 (3.6)	0.83 (1.8)
Aggregate variables			
India wage		-2.75 (1.4)	
India UR		2.32 (1.7)	
Wald(time dummies)	45.5/2 (0.0)	45.5/2 (0.0)[1]	56.5/2 (0.0)
Adj.R_2 [N]	0.95 [42]	0.95 [42]	0.83 [42]
Root MSE	0.010	0.010	0.126
F-statistic	79.07 (0.0)	98.9 (0.0)	33.4 (0.0)
Basmann's F	0.73 (0.40)	0.71 (0.43)	0.90 (0.10)
Dep var mean (s.d.)	9.48 (4.55)	9.48 (4.55)	3.58 (0.27)

Note: The unemployment rate is expressed in proportions in columns 1 and 2 and in percentages in column 3. ([1]): this is the Wald test of the joint significance of India-wage and India-UR.

that the unemployment-wage relation was significantly different in 1972 as compared with the later three years and this motivated us to work with the *reduced sample* (**Section 3.1**). Estimates of the portmanteau equation obtained with the *full sample* are reported in **Table 10** (cols. 1& 3). URUS continues to produce a well-determined equilibrium curve but URDS can no longer be explained in terms of the equilibrium condition underlying perpetual disequilibrium. *(iii)* Although inclusion of the left wing dummy should have taken care of outlier effects, we have re-estimated the MEC with Kerala excluded from the sample (refer **Table 1**) and we find that none of the estimated parameters is significantly changed. This confirms that it alone is not driving the results. *(iv)* Now refer to **Table 11**. In column 1, for reference, is the portmanteau equation from column 1 of **Table 7**. Column 2 reports the same equation with time dummies replaced by the *aggregate wage and unemployment rates* that they were intended to proxy. The idea is to check whether the signs on these aggregate variables are consistent with inter-state migration from high to low unemployment regions. We find that, as expected, the aggregate or 'outside' wage has a negative sign and the outside unemployment rate, a positive sign. *(v)* Since (11) is an equilibrium relation, a positive wage-unemployment relation should show up irrespective of which of the two variables is on the left hand side. Indeed, when the *wage is the dependent variable*, the unemployment rate has a sharp positive coefficient and the amenities reverse their signs (column 3). Positive amenities now imply negative compensating differentials in the wage. Comparison of this equation with the wage-setting equation discussed below emphasizes that we have two distinct structural relations.

4.2. The Wage-Setting Equation

4.2.1. The basic equation

The basic equation using the *daily status unemployment rate* and the *reduced sample* is reported in column 1 of **Table 12**[31]. The regional unemployment rate (*URDS*) has a large and significant negative impact on the regional factory wage. Thus there do exist two

[31] Note that while UR is entered in percentages in the MEC it is expressed in proportions in the wage function.

distinct wage-unemployment relations and they can be identified once they are appropriately specified. Moreover, contrary to popular opinion, factory workers are not entirely insulated from conditions on the market outside. The elasticity of wages with respect to the unemployment rate is -0.24[32].

Although a full set of state dummies is not included here, we have allowed for a range of composition effects that are virtually state fixed effects. We investigate the seriousness of neglecting to control properly for state effects by using the state dummies as instruments for unemployment in the specification that does not include them as regressors. If in fact they should have been in the wage equation then the Basmann test will reject the instrument set. However, the probability associated with Basmann's test (62%) is well out of the range of such suspicion, although it is acknowledged that the Basmann test has a tendency to over-accept (SAS Institute Inc., 1993). The wage equation is estimated on a longer panel of annual data in **Chapter 3** and *true coefficients* on variables other than the *unemployment rate* are obtained. In this chapter, we concentrate on unemployment, for which annual data do not exist, and we must regard -0.24 as an *upper bound* on the true elasticity. Regional *productivity*, *left-wing* and *metropolis* have a significant positive impact on the wage. *Strikes* is insignificant as long as metropolis is in the model. Since union activity is the more conventional wage pressure variable, this lends support to our categorization of *metropolis* as a wage pressure variable. The other effects are discussed in **Section 5**.

4.2.2. Alternative specifications of the wage-setting equation

(i) In **Table 9** (col.2), we report a wage-setting equation estimated with unemployment measured by the *usual status unemployment rate (URUS)*. The unemployment elasticity is -0.28 instead of -0.24 and there is little change in the other coefficients. *(ii)* Recall that investigation of the temporal stability of the slope coefficients in both structural equations demonstrated that the negative wage-unemployment relation is not significantly different between the years. Wage equations estimated on the *full sample* are in **Table 10** (col.1 and

[32] The sample mean of URDS is 0.095.

Table 12
THE WAGE-SETTING EQUATION
2SLS estimates based on the *reduced* sample
Dependent variable=ln(wage)
Unemployment is measured by daily status

	(1)	(2)	(3)
Variant:	**original model**	**replace γ_t with aggregate variables**	**include state fixed effects**
URDS	-2.50 (5.7)	-2.97 (5.5)	-1.70 (1.8)
Wage Push			
productivity	0.47 (5.2)	0.45 (4.7)	
strikes	-0.014 (0.6)	-0.025 (1.0)	
Wage Push & Amenity			
left wing	0.35 (5.3)	0.35 (5.4)	
metropolis	0.16 (3.6)	0.18 (4.4)	
public sector	0.003 (0.2)	-0.022 (1.1)	
Composition			
literacy rate	(+, n.s.)		
higher education	0.18 (1.2)	-0.25 (1.5)	
youth (15-29 yrs)	-1.90 (7.2)	-1.04 (4.6)	
low caste	(+, n.s.)	(+, n.s.)	
Δln (NDP)	0.82 (2.8)	0.59 (1.7)	
Aggregate varibles			
India wage		0.35 (1.9)	
India UR		-1.74 (0.6)	
Wald(time dummies)	20.4/2 (0.0)		29/2 (0.0)
Adj.R_2 [N]	0.85 [42]	0.84 [56]	0.90 [56]
Root MSE	0.108	0.119	0.057
F statistic	30.17 (0.0)	51.0 (0.0)	70.1 (0.0)
Basmann's F	0.87 (0.52)	0.87 (0.52)	0.87 (0.62)

Notes: The mean log wage is 3.58 and its standard deviation is 0.27. The unemployment rates are expressed as proportions rather than percentages.

2). Given a proportionally large gain in degrees of freedom, the estimates are better determined than on the reduced sample. *(iii) The time dummies*, which pick up aggregate variables, are jointly significant at 1% (col.1, **Table 12**). In col.2, we drop the time dummies in the full-sample equation and replace them with the aggregate unemployment rate (*India UR*) and the aggregate wage (*India wage*) (col. 2). The aggregate wage is significant, indicating the importance of factors driving some uniformity in pay between regions. For example, firms with establishments in different states may set wages in both states in accordance with their profits. The aggregate unemployment rate is completely insignificant, which may be interpreted to mean that there is an effective labour market at the level of the state and the notion of such an entity at the aggregate level is undermined.

(iv) As argued earlier, omission of the state fixed effects is unlikely to have serious consequences since we have controlled for what we believe are the most important compositional effects. Nevertheless, in column 3, we report the unemployment coefficient obtained in an equation with a full set of *state fixed effects* in addition to year effects. The unemployment coefficient is smaller and only just significant. The implied elasticity is -0.16. Most other effects in the original equation are wiped out upon inclusion of the 13 dummies.

Table 13
THE UNEMPLOYMENT EFFECT ON WAGES
Estimates for different countries

Country	**(-) unemployment rate coefficient**		**Country**	**(-) unemployment rate coefficient**
Japan	6.40		Ireland*	0.80
India	URDS	URUS	Denmark	0.66
with compositional effects:	2.50	4.70		
with state dummies:	1.70	1.30		
Sweden	2.31		Netherlands*	0.66
France	2.22		Belgium*	0.65
Italy	2.07		Australia	0.56
Norway	1.96		Germany*	0.55
New Zealand*	1.71		Canada	0.50
Austria	1.43		Finland*	0.48
Switzerland*	1.32		USA	0.32
UK	0.98		Spain	0.17

Notes: Adapted from Layard, Nickell and Jackman (1991), Chapter 9, Table 2, p.406. All figures derive from regressions of the log wage on the unemployment rate (in proportions) and other variables. (*) denotes countries where the log of the unemployment rate appears in the wage equation, in which case the reported coefficients are got by dividing the obtained elasticity by the sample mean of the unemployment rate. The figures for India are based on the author's estimates. URDS=daily status and URUS=usual status unemployment rate (**Section 3.3.1**).

While -0.16 is probably closer to the correct value than -0.24, it may be an under-estimate, the true elasticity being difficult to identify without a longer time series. In any case, this estimate is considerably larger than that for a large sample of industrialized nations but smaller than that for Japan[33] (**Table 13**). We do not have other estimates for India or any for other less-industrialized countries. The *size* of the unemployment elasticity depends on two things. One is how well the prevailing unemployment rate represents the difficulty that a new entrant to the pool of unemployed will face in finding a job. It may be an inadequate representation if recruitment from the pool is not random, and there is some evidence that Indian employers tend to hire relatives of current workers (Lal, 1989). The other is the extent to which the prospect of job loss tempers wage demands. This will be modified by factors like the degree of job security and of risk aversion. Job security provisions in Indian factories are deemed to be exceptionally strict by international standards (Fallon and Lucas, 1993)[34]. The appearance of such a large elasticity in spite of these factors suggests the following: The scope and effectiveness of the job security law is fairly small, Indian workers are rather risk averse and/or that there is sufficient turnover and recruitment on the 'open market' that the unemployment rate reflects job prospects.

5. THE REDUCED FORM ESTIMATES

The reduced forms implied by the structural forms estimated in **Section 4** are set out in **Table 14**. They have high explanatory power and tell a rather interesting story.

5.1. What explains regional unemployment?

Reduced form equations for daily (URDS) and usual (URUS) status unemployment are reported in columns 1 and 2, comparison across which provides some useful insights. The unemployment rate in any region is a function of amenity, rural, wage push and compositional variables. The '*left wing* states' of Kerala and West Bengal have an

[33] Japan resembles India in having a large unorganized sector and, associated, large numbers of people readily available for organized sector jobs. Also, benefits in Japan cease after six months.

[34] Recall that the wage here is the factory wage. Job security provisions came into effect in 1979 and from then, until 1982, they applied only to firms with more than 300 workers. Since 1982, they apply to firms with more than 100 workers. However, the vast majority of firms have less than 100 workers (eg., ASI, 1987).

	Table 14 **REDUCED FORM ESTIMATES** ***Explaining unemployment and wage rates*** **OLS estimates on the *reduced* sample**		
	(1)	**(2)**	**(3)**
Dependent variable:	**URDS**	**URUS**	**wage**
Wage push			
productivity	-0.99 (3.0)	-0.25 (0.9)	0.25 (3.6)
strikes	-, n.s.	-, n.s.	-, n.s.
Wage push & Amenity			
left wing	3.18 (9.2)	2.49 (6.2)	0.10 (2.2)
metropolis	2.36 (3.9)	0.89 (1.4)	0.28 (4.3)
public sector	0.23 (3.0)	0.31 (5.4)	-0.003 (0.2)
Amenity			
construction labour	3.61 (7.7)	0.82 (1.7)	-0.35 (3.9)
casual	4.81 (12.1)	1.06 (2.7)	0.084 (1.4)
regular	-4.30 (3.1)	-0.30 (0.3)	0.19 (1.0)
infrastructure	+, n.s.	+,n.s.	-, n.s.
Rural variables			
rural wage	-, n.s.	-, n.s.	+, n.s.
rural unemployment	0.088 (2.6)	0.14 (2.1)	-0.012 (2.1)
landless	1.22 (4.5)	0.46 (1.5)	-0.21 (3.7)
R/U labour force	2.48 (7.1)	1.03 (1.9)	0.22 (3.3)
Composition			
literacy	7.07 (7.0)	2.41 (3.1)	-0.032 (0.3)
higher education	+, n.s.	+, n.s.	+, n.s.
youth (15-29 yrs)	5.6 (3.7)	-2.67 (0.8)	-0.96 (2.2)
caste	-, n.s.	-, n.s.	+, n.s.
Δln (NDP)	-10.95 (9.7)	-5.38 (3.6)	0.68 (3.9)
Adj. R^2 [N]	0.98 [42]	0.93 [42]	0.94 [42]
Root MSE	0.74	0.86	0.085
Wald (TD)	36.3/2	14.7/2	75.3/2
Wald (RHS)	46722/13	600263/13	30592.4/13
Dependent var mean (s.d.)	9.48% (4.55)	5.91% (2.57)	3.58 (0.27)

Notes: Given 14 states, the data cannot support more than 13 independent variables. Therefore, the least significant variable in the reported equation was dropped so that one of the excluded variables could take its place. By this method, we obtained the signs on the excluded variables, all of which are insignificant (or 'n.s.'). See notes to **Table 9**.

unidentified factor that results in unemployment being 3.2% points higher than in other states after controlling for a host of likely influences. One need not draw the conclusion that 'left wing' is 'bad' since, in India, there are worse states of being than unemployment. Moreover, the results indicate that the unemployed gain some utility from staying on in the left wing states. This greater utility may arise from the relatively high development and spread of social infrastructure in them, which is an amenity that we are unable to measure effectively[35]. *Literacy* is an amenity if the literacy rate reflects access to educational facilities. Alternatively, it may be interpreted as reinforcing a queueing model wherein the literate have higher aspirations and so longer search periods[36]. In either case, its positive sign confirms the supply interpretation against a demand-driven story. The role of *public sector* concentration in our model appears to fit the experiment that inspired Harris and Todaro (1970). It was demonstrated in Nairobi that efforts to reduce unemployment by creation of vacancies in the city resulted in a rise in unemployment. Our results suggest that the public sector attracts 'wait unemployment'. A similar idea has been proposed by Lal (1988) in a study of recent employment exchange data and by Krueger in her characterization of rent-seeking for good jobs in India (Krueger, 1974).

Unemployment measured by daily status (URDS) is, *ceteris paribus*, 2.4% points higher in the *metropolitan* states than elsewhere. From our structural form estimates we know that this effect works through wages. The effect on URUS is insignificant. A further wage push effect on unemployment that, again, tells only on the underemployment rate is *productivity*. It is expected to be positive but is negative, which suggests that it may be proxying an uncontrolled compositional effect. By both measures, high unemployment is associated with a prevalence of *casual* and *construction* jobs, though the elasticities are considerably larger for URDS. Not surprisingly, there is a strong negative association of URDS with the share of *regular* jobs. In 1987, only 44% of urban jobs were regular, the fraction ranging from

[35] *Infrastructure* was created to pick up this effect. However, it is is an index that amalgamates various social and economic variables pertaining to rural and urban areas of the states. So, highly developed irrigation systems in one state may counteract educational and health facilities in another. Future work might include more disaggregated indices of infrastructure.

[36] Unfortunately, there are no data on unemployment durations.

33% in Uttar Pradesh to 55% in Maharashtra[37]. Of the remaining workers, 12% are casual and 40% are self-employed workers (Sarvekshana 1990, Statement 6). Though the evidence is not conclusive, the labour market appears to be segmented by these work force categories and the relative sizes of the segments are different across states. So, it is important to control for this heterogeneity. Other aspects of heterogeneity in the work force are *literacy* and *age*. Relatively literate and relatively young populations have higher unemployment rates. As discussed, literacy may be an amenity or a compositional effect (for the latter, see **Table 3**). Controlling for literacy, higher education is insignificant. This is of some interest given the view that much of urban unemployment in India is graduate unemployment (Blaug *et al*, 1969), a view that lives on: 'But then we have yet to see empirical work which demonstrates that urban unemployment rates are extremely high except for particular groups -mainly educated labour- for which specific analysis and diagnosis are called for' (Mazumdar 1984, p. 174). Since 73% of urban males were literate in 1987 (Sarvekshana, 1990), I would not put them aside as a particular group. The age effect is evidently compositional (see **Table 2**). As it is only significant in the URDS equation, it appears that the young experience higher turnover than older workers. The negative caste effect that appears in the structural equation is not significant in the reduced form.

In addition to 'political' (left wing and public sector) and 'structural' (metropolis, job types) features of the state and attributes of its labour force (age, literacy), its rural conditions are significant determinants of its urban unemployment rate. On average, the rural unemployment rate in India is 7.4% (**Table 15**) and therefore cannot be assumed away as in the naive Harris-Todaro model. Inter-state variation in rural UR is also substantial and so the intercept in a cross-sectional equation cannot be expected to control for it. While rural unemployment rates have a positive impact on both measures of unemployment, the proportion of the agricultural labour force that is *landless* raises URDS but not URUS, an intuitive result. The landless appear to be more mobile and to settle for irregular jobs in the

[37] Our estimates show that more regular jobs imply less unemployment, *ceteris paribus*. Since Uttar Pradesh has the lowest unemployment rate among all states, it is striking that it has the least regular employment. This observation underlines the importance of controlling for other factors.

urban sector. Measures of the rural wage are insignificant, possibly on account of its mismeasurement. Our estimates also show that urban unemployment is relatively high in states where the *rural labour force is large relative to the urban.* Finally, in an attempt at isolating the long run equilibrium rates of unemployment, we purge the data of cyclical effects. We find that there is a sharp *cyclical effect* on unemployment, and this is significantly larger for URDS than for URUS. This is of interest because it establishes that cyclical changes impact much more on underemployment than on unemployment, which is consistent with underemployment characterizing the more flexible jobs in the economy.

TABLE 15
RURAL MALE UNEMPLOYMENT RATES BY DAILY STATUS

State	1972/73	1977/78	1983	1987/88	State	1972/73	1977/78	1983	1987/88
Andhra Pradesh	6.4	8.2	7.9	4.9	Orissa	7.1	7.5	7.8	5.0
Assam	2.2	1.6	3.5	4.2	Punjab	4.4	5.2	7.0	3.8
Bihar	8.9	7.6	7.1	3.7	Rajasthan	5.3	3.1	3.5	5.9
Gujarat	6.4	6.2	5.2	4.7	Tamil Nadu	9.4	14.9	17.6	8.4
Haryana	3.3	6.9	6.7	8.3	Uttar Pradesh	3.0	4.0	3.7	3.0
Karnataka	7.4	7.7	6.6	2.5	West Bengal	8.5	9.3	14.4	4.6
Kerala	23.0	25.0	24.3	16.7	Chandigarh	N.A	N.A.	5.7	1.5
Madhya Pradesh	2.4	2.4	2.1	2.3	Delhi	5.9	8.7	11.2	0.9
Maharashtra	7.2	5.9	6.3	2.9	**INDIA**	6.6	7.1	7.5	4.6

Notes: Daily status is defined in the **Data Appendix**. *Sources:* NSS Report, Number 255A (1976), Table 13; Sarvekshana, July-October (1981), Table 14R; Sarvekshana, April (1988), Table 25; and Sarvekshana, Sept. (1990), Statement 41.

5.2. What explains the level of the regional wage?

Wage determination is discussed in fuller detail in the following chapter, where we are able to isolate fixed state effects on wages from time-varying industry-state and state effects. Therefore the discussion here is brief. There is a well-determined negative *age* effect on wages but, somewhat surprisingly, no effect from *literacy*. Neither is there any evidence that the *caste* composition of the state matters. Average factory sector *productivity* is a significant determinant of the average factory wage. Its reduced form elasticity is 0.25 as compared with a structural form elasticity of about 0.50. Controlling, amongst other things, for productivity and literacy, wages are 28% higher in *metropolitan* states. So, there appears to be a city-size effect that, like the firm-size effect (Section 3.1, **Chapter 3**), is not readily explained. However it may be argued to reflect industrial and skill composition and/or the greater facility for worker organization in big cities (see **Section 3.3.2**). A further dummy effect that is difficult to explain arises from *left wing*. The average factory worker stepping across the border from West Bengal to Bihar or from Kerala to Tamil Nadu stands to lose a wage premium of about 10%, other things being equal. Working through the unemployment rate are a positive impact on wages of the *rural relative to the urban labour force* and negative effects from the share of *construction* workers in the urban sector as well as from *rural unemployment* and *landless*. *Casual* and *regular* are insignificant. Contrary to popular opinion, there is no evidence here that the *public sector* pays higher wages, at least once other things are held constant. Finally, wages appear to be *procyclical.*

6. CONCLUDING REMARKS

This study was motivated by the phenomenon of large and stable disparities in unemployment rates across the Indian states. The question is approached by investigating the equilibrium properties of the data. The chapter has three main parts. The first is the development of the theoretical and empirical models. This is followed by identification of the structural forms and that, by an explanation of unemployment and wage rates based on the estimated reduced form parameters.

The analysis is based on a model of the long run equilibrium in a regional labour market. The long run is a period long enough to permit migration and the urban sector of any state shares 'migration routes' with its rural hinterland and with the urban sectors of other states. In this three-sector framework, we have investigated the alternative hypotheses of global equilibrium and perpetual disequilibrium. The evidence favours the latter. In other words, the slow convergence of urban unemployment rates across India appears to arise on account of the interaction of every urban labour market with its rural counterpart. The rural sector has a large reserve of labour and the urban sector is unable to 'run away' from its rural sector. This, we assume, is because rural-urban migration within states is more rapid than inter-state urban-urban migration. Some support for this assumption is gained by identification of a no-arbitrage condition between the rural and urban labour markets. Were barriers (or costs) to rural-urban migration significant, the condition would give a band rather than a line and our estimates would have been poorly determined.

The rural-urban equilibrium is identified by estimation of a generalized Harris-Todaro model. Given the importance of this construct in the literature on less industrialized economies, well-determined estimates of it are of some independent interest. Like Harris and Todaro, we neglect to control for amenity differentials because we do not have the required data. Our claim that there exists a rural-urban equilibrium is robust to this omission. Controlling for the amenity differential would strengthen the positive unemployment-wage relation. Yet, future work in this direction might obtain some measures of rural and urban amenities from, for example, the decennial census. We have also estimated an inter-state migration equilibrium condition but we find no evidence there of the unemployment rate in a state being systematically related to its pecuniary opportunities. Instead, there is a disequilibrium between states but, by the foregoing argument, we can do better than relegate the explanation of this to migration barriers between states.

An equilibrium curve is obtained under the perpetual disequilibrium hypothesis by setting the volume of migration in from the rural sector equal to the volume of migration out to other urban sectors[38]. In the regional labour market, there is, in addition, a wage-setting curve that determines where along the migration equilibrium curve the labour market equilibrates. An important aspect of this analysis is that we are able to identify both the wage function and the migration equilibrium condition. Within any region, a 1% point rise in the unemployment rate causes the wage to fall by an amount that lies between 1.7 and 4.7%[39]. At the same time, if a region sports a positive wage differential of 10%, it attracts 'wait' unemployment of the order of 0.25% points[40].

The long run unemployment rate in a region is determined by wage-setting behaviour in the region and by migration between regions. The reduced form unemployment equation shows that long-run differentials in unemployment rates between regions can be explained in terms of differential wage-push, productivity, amenities, and labour-force composition. All of these factors exhibit considerable variation across the Indian states. The variables that contribute significantly to explaining unemployment are left wing, public sector, literacy, rural unemployment, rural/urban labour force and the proportion of casual and construction

[38] The empirical translation of this curve encompasses the terms that appear in the intra and inter-state migration equilibrium conditions.

[39] More precisely, the usual status unemployment rate causes the wage to decline by 1.3-4.7% and the daily status rate by 1.7-2.8%. The smaller number in each case is the estimate obtained with a full set of state dummies in the model and the larger number is that obtained when a set of compositional variables is included. Unfortunately, in the absence of a longer time series on unemployment rates, it is not possible to be more precise than this.

[40] There is enormous regional variation in wages (Section 2.1, **Chapter 3**).

workers in the urban sector (variables defined in **Data Appendix**). Additional variables that impact only on the broad measure of unemployment, that includes underemployment, are metropolis, age and the proportions of regular urban workers and landless rural workers. These results are obtained after controlling for aggregate influences on the urban unemployment rate and for the fact that cyclical movements of NDP are not perfectly synchronized across states. In the reduced form wage equation, wage pressure variables have a positive impact and amenities appear as negative compensating differentials. Wages are higher in left-wing, metropolitan and high-productivity states. Interestingly, the public sector does not pay relatively high wages. Working through the migration condition, construction labour, rural unemployment and landless have a depressing influence on wages and there is a negative compositional effect from age. Although the smallness of the data sample deems that the results be regarded as tentative, they are altogether very plausible.

For tangibility, consider the case of Kerala where one in five people is unemployed or underemployed. Application of our model to realities in Kerala would suggest that this is the outcome of a high degree of *wage push* stemming from high levels of education and unionization, combined with relatively good *amenities* in the shape of health and education provisions. These are factors that, unlike demand, are slow to change and thus generate an explanation that is consistent with the observed persistence of the relatively high unemployment rate in Kerala. What may appear as a competing hypothesis regarding unusually high unemployment in Kerala is that capital is unwilling to locate there because the climate of labour relations is adverse to the interests of capital (eg., Kannan, 1992). Consequently, there are few new jobs. This is a demand explanation that may well pull weight. However, while it explains why capital does not enter the state, the question of why labour does not leave still has to be answered.

The analysis consistently uses two measures of unemployment. The daily status measure is a personday rate that includes underemployment, the dimensions of which are significant in India. The usual status rate is a narrower measure that picks up only long durations of unemployment, where *long* refers to most of a year. A potentially important difficulty with the empirical analysis is that, on the basis of existing field surveys, it is unclear which urban wage matters to potential migrants. We have specified the wage as a weighted average of the wage in regular, casual and self-employment. This has the advantage of allowing the data to find the correct weights. However, it has the disadvantage that, lacking data on the incomes of casual and self-employed workers, we have had to assume that these incomes are a constant fraction of the income of regular workers.

Workers' utility is allowed to depend on amenities or non-economic factors specific to regions. Amenities are distinguished from migration barriers or costs. We have averted the problem of measuring costs by investigating the equilibrium structure of unemployment in the long run, in which time span the inhibiting role of costs is expected to be small. While explorations of labour market equilibria across U.S. regions have specified amenities in terms of inches of rainfall and area coverage of parks (eg. Hall 1972, Marston 1985), we specify amenities relevant to migration behaviour in India in terms of job security (public sector), social infrastructure (infrastructure, education), low risk of prolonged unemployment (metropolis) and ease of entry (casual, construction). However we are not able to obtain effective measures of all of the variables we think matter (eg, infrastructure includes rural and urban and economic and social infrastructure; it is not clear what the dummies pick up). Finally, we allow for segmentation of the labour market by job-type, allowing for different intercepts in the migration equilibrium condition for different types of workers such as casual and regular or literate and illiterate workers.

So far, we have not considered the policy implications of our findings. In a two-sector model, if barriers significantly slow down the speed of adjustment, then there is a case for policies directed at stimulating demand in the depressed region. In the context of a dual economy, this has been suggested, amongst others, by Stiglitz 1974, Bhagwati and Srinivasan 1974 and Blomqvist 1978. However, if migration along a utility gradient brings the regions into equilibrium fairly rapidly, then this policy is ineffective. It is the latter view that inspired the Harris-Todaro model. Our finding that the urban sectors of different states are in disequilibrium with one another would imply a case for employment or investment subsidies in the high-unemployment states. However, our analysis suggests that this, on its own, will not work to reduce urban unemployment because job creation will attract an excess (relative to the new jobs) of rural migrants. What, then, can be done? Our view is that, given *effective* barriers between states, attempts at job creation concentrated in the high unemployment states are preferable to *laissez faire*[41]. We now consider if it matters whether it is the rural or the urban sector of the high unemployment state that is stimulated by the intervention. If one is worried about within-state rural-urban flows maintaining urban unemployment, then job creation should be concentrated in rural areas. This was what Harris and Todaro proposed. However, recognizing the extent of landlessness and unemployment in the rural sector (which HT did not), one could argue that urban unemployment is no worse than rural unemployment. In view of a greater diversity of job options and better developed public infrastructure in the urban sector, it might be said that the more distressful unemployment is experienced in the rural sector. In that case, one might direct resources at urban job creation, allowing the rural unemployed to spill over as urban job-seekers. Fields (1975) proposed improving availability of information regarding urban jobs so that rural dwellers need not migrate to an urban area without a job in hand. This could accompany the subsidies we propose.

[41] We mean, here, states with high *urban* unemployment rates. As a matter of fact, there is a strong positive correlation of the state rankings of rural and urban unemployment rates, so that speaking of a high unemployment state is not ambiguous. We neglect the question of financing of subsidies, though it could be compelling: Basu (1992) highlights this problem in a Harris-Todaro economy, concluding that, for the magnitude of the subsidy that will typically be required, hyper-inflationary processes are bound to develop.

Table A1

PERSISTENCE OF THE REGIONAL PATTERN OF UNEMPLOYMENT RATES

Spearman's rank correlation coefficients

Year	1972/3	1977/8	1983	1987/8
1972/3	1.00 (0.00)			
1977/8	0.87 (0.0001)	1.00 (0.00)		
1983	0.86 (0.0001)	0.77 (0.0002)	1.00 (0.00)	
1987/8	0.87 (0.0001)	0.68 (0.0017)	0.88 (0.0001)	1.00 (0.00)

Notes: The unemployment rate is the *daily status* rate. The probability that the observed correlation is zero appears in parentheses. *Source:* The unemployment rates are published in various issues of *Sarvekshana*, the NSSO Journal.

Table A2

UNEMPLOYMENT RATES IN INDIA

The Daily, Weekly and Usual Status Measures

Daily status	rural males	rural females	urban males	urban females
1972/73	6.8	11.2	8.0	13.7
1977/78	7.1	9.2	9.4	14.5
1983	7.5	9.0	9.2	11.0
1987/88	4.6	6.7	8.8	12.0
Weekly status				
1961/62	3.7	8.5	3.0	3.3
1972/73	3.0	5.5	6.0	9.2
1977/78	3.6	4.0	7.1	10.9
1983	3.7	4.3	6.7	7.5
1987/88	4.2	4.3	6.6	9.2
Usual status (adjusted)				
1972/73	1.2 (1.5)	0.5 (0.3)	4.8 (1.6)	6.0 (0.5)
1977/78	1.3 (1.8)	2.0 (1.8)	5.4 (2.0)	12.4 (1.3)
1983	1.4 (2.2)	0.7 (0.5)	5.1 (2.5)	4.9 (0.6)
1987/88	1.8 (3.0)	2.4 (2.3)	5.2 (3.0)	6.2 (1.0)
Usual status (unadj.)				
1977/78	2.2 (3.1)	5.5 (3.5)	6.5 (2.3)	17.8 (1.6)
1983	2.1 (3.2)	1.4 (0.9)	5.9 (2.9)	6.9 (0.7)
1987/88	2.8 (4.5)	3.5 (2.6)	6.1 (3.5)	8.5 (1.1)

Notes: Figures in parentheses are the numbers unemployed in millions. Sources: Sarvekshana, Journal of the National Sample Survey Organization, April 1988 and September 1990.

CHAPTER 3
INDUSTRIAL WAGE DETERMINATION

PART 1: INTRODUCTION

1.1. ON WHAT IS DONE AND WHY

In **Chapter 2** we investigated the equilibrium properties of the geographic distribution of unemployment, focusing on the *behaviour of workers*. In the long run, unemployed workers in a certain region *'choose'* to be unemployed in the sense that they have the option to move to regions where their chances of getting a job are brighter. Now we are interested in why there is *involuntary* unemployment, and so we must move into the short run where this is determined. But understanding wage determination is fundamental to understanding a non-clearing labour market. Therefore, in this chapter, we investigate the short run 'supply curve', or the wage setting function[1].

This was estimated on data pertaining to regional aggregates, in **Chapter 2**, and the central result was that the wage bends under the pressure of unemployment. The emphasis is now shifted to the fact that the wage does not bend *enough* to eliminate unemployment. This puts the *behaviour of employers* in focus. Why don't employers lower the wage, given that there will be takers in the presence of substantial unemployment ? The answer to this question lies in knowing how wages are set. Clearly, either employers deviate from profit-maximization, or cutting the wage will lower their profits. The first view is incorporated in rent-sharing theories of wage determination and the second in efficiency wage models. Both offer non-competitive models of the wage-setting process.

[1] The wage setting function is the imperfect competition analogue of the short run labour supply curve. It is not really a supply curve because there is no such thing if wages are not 'givens' on the market. See Layard, Nickell and Jackman (1991, pp.20-21) for an account of the conceptual difference between the wage-setting function and the competitive labour supply curve.

Non-competitive elements of wage determination typically relate to enterprise or industry specific features, for example, size or profits. Therefore, not only unemployment but a wage distribution is generated. This gives rise to the notion of *good jobs and bad jobs*, quite independently of good workers and bad workers. If there is one dominant axis along which good jobs are discriminated from bad jobs, this would appear to be the production *technology*, rather like *amenities* discriminate between good and bad regions. This means that it is important to capture technology effects on wages. Compared with the regional panel used in **Chapter 2**, the data panel that is used in this chapter has the important advantage that it allows us to control for industry specific fixed and trend effects.

The other major advantage of the data used here is that we have 9 years of continuous annual data as against 4 years of quinquennial data. With the additional degrees of freedom in the time dimension, we are able to estimate the *true coefficients* on the included time-varying variables. Thus, the coefficient on productivity in the regional wage equation of the previous chapter represents a mixture of effects stemming from productivity variations and from purely cross-sectional variables that are correlated with productivity. In contrast, the wage equation estimated in this chapter gives us the true coefficient on productivity and the other explanatory variables. As the coefficient on productivity in the wage-setting equation is the insider weight, it is important to have a correct estimate of it. However, these gains from using the longer panel come at the cost of losing the unemployment variable. As described in **Chapter 2**, there are no time series data on unemployment rates in India, whether by region, or for the country as a whole. This is unfortunate even though, as we shall argue, the estimated equation incorporates proxies that control quite effectively for unemployment.

In sum, we estimate a wage-setting equation on an industry-region panel of data, with the motivation of understanding involuntary unemployment. We attempt to quantify the weight of non-competitive factors in explaining wage variation. The chapter is divided into five parts. **Part 1** introduces the motivation, existing research on the subject, and relevant contextual features. In **Part 2** we document the evidence on industry and regional wage differentials in India, and offer some interpretations of the data. We then proceed, in **Part 3**, to set out a very general model of wage determination that incorporates the stylized features uncovered in Part 2. This model is estimated on an industry-region panel that pertains to India's registered manufacturing sector in the 1980s, and the results are discussed in some detail. In **Part 4**, we present a decomposition of wage variation by each of the three dimensions in the data: industry, state and time. Finally, in **Part 5**, we summarize our results and conclude.

1.2. WHAT WE KNOW ABOUT WAGE DETERMINATION IN INDIA

The literature on wage determination in India[2] consists of a scatter of empirical studies with correlations or simple least squares regressions, mostly on time series data, establishing that wages, productivity, capital intensity, and the cost of living are positively correlated[3]. In contrast to this rather dull collection are some gems of field studies (see, for instance, Harriss, Kannan and Rodgers 1990, Deshpande and Deshpande 1989 and Papola and Subramanian, 1975). Altogether, there is a paucity of theoretical work, or indeed, attempts to defend or challenge existing theories. In this terrain are two landmarks. The first is an old debate over institutional versus subsistence wage theories, which is discussed in some detail in Bhalotra (1989). The second, implicitly taking its point of departure from the first, is a collection of papers by Mazumdar (1973, 1988) based on a survey of Bombay workers, and advancing the size hypothesis. We now consider both.

Subsistence

India's industrial labour market is distinguished from that in the more industrialized economies by its relative abundance of labour. This has led to the view that manufacturing wages are determined by subsistence requirements, and the manufacturing wage only exceeds the agricultural wage by a cost of living adjustment factor (eg., Palekar, 1962). A

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[2] As in the rest of this thesis, unqualified reference to wages implies reference to factory sector wages.

[3] See, for example, Brown (1962), Johri and Agarwal (1966), Sinha and Sawhney (1970), Papola (1971), Verma (1972), Johri and Misra (1973), Dholakia (1976), Madan (1977).

presumption of this nature underlies the Lewis (1954) model of the development process. However, evidence of secular growth in real earnings[4] is inconsistent with this, given that the labour surplus is far from having been eradicated. The existence of substantial inter-industry wage differentials (**Section 2.2**) also belies the *surplus labour model* for the simple reason that subsistence requirements do not differ systematically between industries unless the industries are regionally concentrated and the cost of living differs systematically across regions. However, we use industry data disaggregated by region and deflate wages by a regional index of the cost of living, but huge industry differentials persist.

Institutions

The subsistence wage theory was superseded by the view that factory wages in India are institutionally determined (eg., Ghosh 1966, Jackson 1972, Sengupta 1988, World Bank 1989, Ahluwalia 1991). This assumption is commonly made in theorizing about developing economies (eg., Harris and Todaro, 1970). In both the Indian and LIE literature, the suggestion is that institutions *alone* can explain the wage path fairly accurately. In India, the wage-setting *institutions* to which reference is made are mainly wage boards and trade unions. *Wage boards* were set up in 1957 to recommend norms for wage setting. They introduced the notion of a *fair wage*, something between a subsistence wage and a wage determined by the firm's ability to pay. However, they were confined to a limited number of industries (eg., cement, sugar, textiles) and their recommendations were not statutory but up to the state government to implement. Although they have probably contributed to smoothing regional differentials in wages within selected industries, they are unlikely to have played a significant role in shaping wages (see Sinha (1971), NCL (1969), Johri (1967) and Papola (1970)). Other government interventions in the labour market, such as minimum wage legislation, are deemed to be even weaker influences on the wage[5].

On the basis of empirical studies that have investigated the effects of *union power* on wages,

[4] See Sawhney (1976), Madan (1977) and Tulpule and Dutta (1988) for evidence on this.

[5] A comprehensive account of the state machinery directed at regulating wages is provided in World Bank (1989) and Bhalotra (1989).

the significance and direction of such effects appears ambiguous[6]. In an earlier study (Bhalotra, 1989), we estimated industry-level wage equations on time series data (1960-85). We found a positive effect of *membership density* on earnings in 6 of 17 industry groups [Chemicals, Cement, Metal products, Petroleum, Tobacco, and Sugar (part of Food)] and a negative effect in two [Rubber and Shipbuilding]. *Days lost per employee, dispute frequency per establishment* and the *average length of disputes* were investigated as alternative union variables. The results were mixed, the strongest discernible pattern being a negative impact of dispute frequency on earnings in 4 of the 17 sectors. Therefore, the evidence is not strong in favour of union effects on wages. Since both trade unions and government interventions hold sway only in the factory sector, the institutional view has claimed support from the fact that there is a large differential between *factory and non-factory sector* wages. However, as we shall see, this evidence is undermined by the observation that there are equally large wage differentials *within the factory sector*, that are not correlated with any institutional differences.

Firm size

Mazumdar (1988) has carefully analyzed data on manufacturing establishments in Bombay in 1978. This shows that, in progressing from casual workers to workers in small-units and thence to workers in large-units, one finds a continuum of wage rates. There is no break at the 'walls' of the factory sector ($10/20^+$ workers; see **Data Appendix**). The break, if there is one, is where establishment size exceeds 100 workers. This result is obtained after controlling for a range of personal and job characteristics, including occupation, age, education, training and language. This strikes us as persuasive evidence against the *primacy* of union power and labour legislation in explaining wage differentials. If institutional forces were paramount, one would expect to see a cut-off around the boundaries of the factory sector but instead, there is enormous size-related variation in earnings *within* this sector.

[6] See Verma (1970, 1972), Sinha and Sawhney (1970), Palekar (1962), Fonseca (1964), Johri (1967), Lucas (1988), and Bhalotra (1989). It is difficult to create a statistical measure of the effective power of unions in the wage bargain, and many of the cited studies do not control for reverse causality.

Table 1.1a The Size-Earnings Relation *Survey evidence for selected firms*					
Employment size	**Machine tools**	**Powerloom**	**Printing**	**Shoes**	**Soap**
1-10	2172		2364		2664
11-25	2316	1140	2436	2256	2832
26-50	2700	1428	2604	3000	2964
51+	2544	2244	2292		3240

Notes: The figures are average annual wages of unskilled workers in rupees. *Source:* World Bank Surveys, 1979-80. Cited in Mazumdar, 1984.

The secondary role of institutional factors is reinforced by looking at history. Mazumdar (1973) reports evidence of large wage differentials in pre-Independence India, which is significant because institutional forces have only become prominent in the post-Independence period. For example, in 1892, factory wages were higher than in other activities in the urban economy and also higher than in agriculture. **Table 1.1a** shows a positive size-wage relation for unskilled workers in a range of firms. There is evidence of graduation with size even for narrow intervals at the small end of the distribution. In **Table 1.1b** we present per worker earnings by size class of firm for the factory sector. Note that these are these are the 'gross' size differentials, that is, worker and job characteristics have not been held constant[7].

Table 1.1b The Size-Earnings Relation *Average factory sector data*			
Size	*Earnings*	*Size*	*Earnings*
0-49	6457.30	500-999	17067.00
50-99	7331.10	1000-1999	20060.70
100-199	8693.50	2000-4999	20665.90
200-499	12951.20	5000+	20852.30

Source: Summary results for the factory sector, Annual Survey of Industries (ASI), 1986-87, Statement 6. The data refer to 1986. Size is in terms of employment and earnings are in rupees.

[7] Mazumdar (1988) specified the following categories: casual, small, 10-99, 100-499, 500-999 and 1000+ workers. He does not report the average wage for each category, only the results of a multiple classification analysis.

In ousting the institutional hypothesis with the size hypothesis, it should be noted that size is positively correlated with the institutional influences on wages. The Factories Act (1948) requires firms with more than 10 or 20 workers to register. This effectively limits the scope of labour legislation to such firms, the small unregistered firms being difficult to monitor. Some legislation is explicitly limited to the bigger firms within the factory sector. For example, job security provisions only apply to firms with more than 100 workers. In addition, worker-organization is more likely in larger establishments, and there is evidence for India that workers in larger firms are more powerful (Verma 1970, Deshpande 1992[8]). However, the finding that wage differentials do not observe the union/non-union (or, equivalently, factory/ non-factory) divide, along with the cited historical evidence, seems to us to outweigh the worth of simple correlations (eg, between union density and wages) that have no power to distinguish proximate from ultimate causes.

Interpretation of the size-wage effect

The fact that establishment size provides the dominant explanation of cross-sectional variation in wages is a good lead, but it is not entirely satisfactory unless it can be given some behavioural underpinnings. The size-wage effect has been observed in enough empirical studies in the international domain to have earned the status of a stylized fact (see Brown and Medoff, 1989). However, there is no clear understanding of the effect and it can be reconciled with more than one existing theory. For example, if larger firms face potentially higher monitoring costs, the size-wage effect can be encompassed by an *efficiency wage* mechanism. Alternatively, it is consistent with *rent sharing* if larger firms earn larger rents. This is plausible because they tend to have bigger market shares and to face lower borrowing costs, given capital market imperfections. The status of this explanation is somewhat weakened by the preceding discussion, where it was argued that the role of unions is probably secondary. The size effect on wages is also consistent with *competitive* wage determination if larger firms typically have better quality workers or worse working conditions, such as the alienation experienced in a large work place. Since the size

[8] Deshpande (1992, p.95) records evidence from a survey in Bombay in 1989, that shows a clear tendency for unionism to rise with firm size. Among firms with less than 50 workers, not even a quarter belong to unions but in large firms, union density ranged from 40-82%, the highest figure being in firms employing more than 5000 workers.

effect reported by Mazumdar is obtained after controlling for worker attributes, a competitive explanation of the size effect in India must rely on job characteristics and unobserved worker quality. Using U.S. data, Brown and Medoff (1989) provide a thorough investigation of alternative hypotheses, but conclude that the size effect persists as something of a mystery. In particular, the observations that size affects the wage change of workers moving between firms of different sizes, and that different occupational groups earn similar size premia, undermine the competitive hypothesis.

In conclusion, the inadequacy of the institutional explanation implies that there are important economic forces at work. The existence of size-wage effects is interesting in itself, but it does not help discern whether the economic forces are competitive or not. However, the empirical studies of industrial wage determination in India in the 1960s and 1970s quite consistently find a strong positive correlation of wages with productivity and capital intensity. Although this *could* be on account of uncontrolled quality factors, it is suggestive of non-competitive forces. The existence of large inter-industry wage differentials (**Part 2** of this chapter), the presence of substantial unemployment (**Chapter 2**), and the labour market segmentation implicit in the rural-urban and informal-formal sector dualisms reinforce this suggestion. In any case, as an assumption of perfect competition is restrictive, we start out with some favour for the view that wages are set primarily on the basis of economic considerations moulded by imperfectly competitive markets. In the rest of this chapter, we seek to consolidate the evidence in support of this view.

PART 2: INTER-SECTORAL WAGE DIFFERENTIALS

In this section we report the evidence on inter-sectoral wage differentials in our data (**Sections 2.1** and **2.2**). In **Section 2.3**, we present some evidence from other countries, developing (LIEs) and developed (IEs), along with interpretations that may be drawn from the gamut of the evidence. The sample consists of production workers in factories, a relatively homogeneous occupational group. A major limitation in interpretation of our differentials is that, in the absence of micro-data, we are unable to control for the personal characteristics of workers. Working with U.S. micro-data, Krueger and Summers (1987) estimate industry wage differentials with and without controls for personal and demographic characteristics. They report that although the controls result in some tightening of the wage structure, they leave the ranking of industries unchanged. On this basis, they make international comparisons of the wage structure using unadjusted data. Their experiment increases the reliability of the interpretations proffered here.

2.1. INTER-REGION WAGE DIFFERENTIALS IN INDIA

Table 2.1, column 1 reports the percentage deviation in state earnings from the India average. In the 1980s, nominal earnings in Andhra Pradesh were almost 50% below the country-average and those in Maharashtra, almost 50% above. Thus earnings in Maharashtra were thrice earnings in Andhra, with which it shares its south-eastern border. This is a fantastic range for neighbouring states. These differentials have shown no tendency to narrow between 1979 and 1989. The *weighted* standard deviation (henceforth, s.d.) of logged state wages[9] remained at about 32% until 1986, after which year it displayed a modest upward tendency upto 1989, the last year for which data are available.

From **Table 2.2** it appears that productivity, work intensity and factory size contribute

[9] The s.d. of log W is approximately equal to the coefficient of variation (c.v.) of W when it is small. Let $E(W)=\mu$. Then $\ln X= \ln \mu + \ln[1+(1/\mu)(W-\mu)] \approx \ln \mu + (1/\mu)(W-\mu)$, from which it follows that $s.d.(\ln W) \approx (1/\mu)s.d.(W) = c.v.(W)$.

significantly to explaining the state earnings structure. But are the variables in **Table 2.2** merely proxying *industrial composition* ? At first glance, this appears to be the one

Table 2.1
STATE WAGE DIFFERENTIALS

	(1)	(2)	(3)
State	***Composition variable***	***Composition constant***	***s.d. of log earnings***
Andhra	-48.85	-20.62	0.593
Kerala	-33.38	24.89	0.831
Punjab	-16.34	-15.57	0.241
Uttar Pradesh	- 9.10	- 2.56	0.426
Tamil Nadu	- 6.18	- 4.50	0.467
Haryana	- 5.90	- 5.56	0.307
Gujarat	- 2.64	-12.76	0.345
Karnataka	3.08	0.13	0.430
Delhi	3.13	0.11	0.291
Madhya	5.62	- 8.51	0.584
Rajasthan	10.19	2.68	0.294
Orissa	29.99	-19.34	0.633
Bihar	31.00	3.38	0.481
West Bengal	42.63	39.74	0.334
Maharashtra	49.40	42.00	0.360
weighted s.d.(logs)	0.316	0.203	

Notes: Figures in *col.1& 2* are in percentages. The differentials refer to nominal earnings per worker and are computed as deviations from the mean, using $[\exp(\Delta w)-1]*100$, where $\Delta w=(\ln w_s - \ln w)$, w_s=state wage & w=India wage, both averaged over 1979-87. In col. 1, $w_s=\Sigma_i(N_{is}/N_s)w_{is}$ and in col.2, $w_s=\Sigma_i(N_i/N)w_{is}$, where in each case the data are averaged over time without weights, subscript 'i' denotes industry and no subscript denotes the all-India average. Figures in the last row are the weighted standard deviations of logged state wages, obtained as $\sigma=\Sigma_s(N_s/N)[w_s-w]^2$ and $\Sigma_s[w_s-w]^2$, respectively. *Col.3* shows industry dispersion within each state.

systematic element underlying the state ranking. Thus Andhra and Kerala are dominated by Leather and Wood respectively, both of which are low-wage industries. At the other end of the spectrum, Bihar and Orissa have a concentration of the heavy basic metals industries and Maharashtra has the 'sunrise' (growing) petrochemical group. To investigate this question, the state variation in these variables is re-computed, controlling for compositional differences. This is done in the weighting scheme, by forcing all states to have the average (India) employment composition (col.2, **Table 2.1**). The *adjusted* state data have some interesting properties, which we now discuss.

(a) There remains substantial inter-state variation, the s.d. of adjusted log earnings being 20%. This indicates that *pure* state effects, or state effects that are independent of industrial composition, are of considerable magnitude. The magnitude of pure state effects on earnings is reinforced by the data in col.3 of **Table 2.4**, which shows the degree of dispersion of earnings in *each* industry, across states. For example, the standard deviation of Chemical wages is approximately 45% of its mean. Therefore, in an analysis of industrial wages in India, controlling for location effects may be rather important. The econometric analysis to follow (**Part 3**) takes this into account.

Table 2.2
Correlates of Average State Earnings

	earnings	days/worker	productivity	factory size (N)	factory size (K)
earnings	1.00 [1.00]	0.72* [0.58*]	0.82* [0.44**]	0.40 [0.26]	0.73* [0.26]
days/worker		1.00 [1.00]	0.55* [0.14]	0.44** [0.35]	0.54* [-0.01]
productivity			1.00 [1.00]	0.15 [-0.22]	0.71* [0.59*]
factory size (N)				1.00 [1.00]	0.70* [-0.25]
factory size (K)					1.00 [1.00]

Notes: These are Pearson correlation coefficients for data averaged over 1979-87. In each cell, the first number is the correlation with unadjusted data and, in square brackets, is the correlation with adjusted data. Unadjusted $x_s=\Sigma_i[(N_{is}/N_s)x_{is}$, and adjusted $z_s=\Sigma_i[(N_i/N)z_{is}$; where $x_{is}=(1/T)(\Sigma_t x_{ist})$ and $z_{is}=(1/T)(\Sigma_t z_{ist})$. Each variable is a vector of 15 observations, one for each state in the sample. Earnings and productivity are nominal values. Productivity is value added per worker. Factory size is either average employees (N) or average fixed capital stock (K) per factory. *=significant at 5% and **=significant at 10%.

(b) Controlling for industrial composition has reduced earnings dispersion from 32% to 20%. It appears that composition effects work in the direction of widening the extant earnings structure. Thus, not only is it meaningful to speak of *inherently* low-wage states, but it appears that low-wage industries are attracted to low-wage states, and vice versa. This would make sense if, for example, inherently low-wage regions had populations with low education and skill levels. In **Section 4.2**, we make an attempt at identifying factors that underlie the pure state effects on wages (**Table 4.4a**).

(c) The correlation coefficient between the unadjusted and adjusted earnings structures is

0.65, which is significant at 1% (N=15). Nevertheless, the composition controls generate two interesting movements in the earnings structure. *Kerala* is second from the bottom on account of its industrial composition. When this is controlled for, her wages are third from the top. Thus, workers in the two high-unemployment states, Kerala and West Bengal, *do* get above-average wages, a fact that is masked when looking at the unadjusted data. The other very striking change is in *Orissa.* In direct contrast to Kerala, observed earnings in Orissa are 30% above average, but once its industrial composition is controlled for, its earnings show up as being 15% below average.

(d) Pairwise correlations of the adjusted variables are in square brackets in **Table 2.2.** Composition-adjusted earnings vary independently of size, but are significantly correlated with composition-adjusted productivity and days worked. This suggests that the pure state variation in earnings is not random, but rather, is underpinned by systematic forces.

2.2. INTER-INDUSTRY WAGE DIFFERENTIALS IN INDIA

Earnings differentials between industries are even greater than between regions. **Table 2.3** reports the percentage deviation in industry earnings from the manufacturing average (col. 1). Over the period, 1979-1987, nominal earnings in the Transport equipment industry are four and a half times those of workers in the Tobacco & Beverages industry. The standard deviation of log earnings is 46%, as against 32% for state earnings. This is far greater than the inter-industry earnings dispersion in a diverse set of other countries (**Table 2.6**), and yet, to our knowledge, has been completely unexplored. Like state dispersion, industry dispersion is fairly *constant* until 1986, when it displays an upward tendency.

The industry earnings ranking fits nicely with the loose impression that relatively high wages are paid by industries that are capital and/or technology intensive. Such industries typically have relatively high levels of output per worker, and the share of labour in total costs is relatively small (Marshall's importance of being unimportant). Both factors make it more likely that enterprises in these industries can afford to offer higher wages than others. **Table 2.4** shows that earnings are significantly correlated with work intensity, productivity, and average factory size. Does the picture change in any significant way if we control for *location effects* on earnings? Refer column 2, **Table 2.3**. The differentials are narrowed without there being a significant change in the industry ranks. The degree of dispersion is down from 46% to 36%. Consistent with the parallel analysis of state earnings,

Table 2.3
INDUSTRY WAGE DIFFERENTIALS

	(1)	**(2)**	**(3)**
Industry	**Location variable**	**Location constant**	**s.d. of log earnings**
Tobacco & Beverages	-63.28	-42.16	0.388
Food Products	-48.00	-45.03	0.339
Wood & Furniture	-41.81	-42.08	0.166
Textile products	-31.76	-34.56	0.400
Cement, glass etc	-22.48	-18.43	0.258
Leather & Fur	-13.74	-17.59	0.279
Metal Products	4.38	- 7.41	0.381
Wool & silk textiles	9.99	6.09	0.285
Cotton textiles	11.89	5.25	0.175
Miscelleneous	14.58	0.14	0.366
Paper & Publishing	20.06	15.55	0.173
Petroleum & Rubber	25.44	11.48	0.289
Chemical Products	35.18	33.99	0.451
Non-Elec Machinery	36.42	33.87	0.247
Electricity Generation	46.28	47.77	0.191
Basic metals	51.76	27.16	0.370
Electrical Machinery	54.08	45.37	0.261
Transport Equipment	63.03	52.73	0.268
weighted s.d.(logs)	0.462	0.360	

Notes: See Notes to **Table 2.1**, replacing state with industry. Col. 3 shows the geographic dispersion of earnings within each industry group. Average industry earnings are obtained as $w_i=\Sigma_s(N_{is}/N_i)w_{is}$, where the earnings (w) and employment (N) data have been averaged over time. Then the standard deviation of state earnings around the industry mean is $\sigma=\Sigma_s(N_{is}/N_i)[w_{is}-w_i]^2$.

the narrowing indicates that location effects work in the same direction as the forces underlying the extant or location-constant earnings structure. The correlation between unadjusted and adjusted earnings is 0.975. From this it is evident that region effects on the industry distribution are rather weaker than industrial composition effects on the regional distribution of earnings. This is underlined by a comparison of columns 3 in **Tables 2.1** and **2.3**. **Table 2.1** shows that the dispersion of industry earnings *within* half of the states is greater than the all-India industry dispersion. Strikingly, the s.d. of log earnings in Kerala is approximately 83% of its mean. Clearly industry-specific factors within any given region drive a sharp wedge in the wage distribution. Although location effects can account for some of the inter-industry variation in earnings, there remains an enormous dispersion (36%) to be explained. In the analysis to follow, we investigate the precise influence of the correlates of earnings in **Table 2.4** (**Part 3**) and consider their weight in an explanation of the observed variation in wages (**Part 4**).

Table 2.4
Correlates of Average Industry Earnings

	earnings	days/worker	productivity	factory size (N)	factory size (K)
earnings	1.00	0.79	0.88	0.43	0.64
days/worker		1.00	0.65	0.48	0.62
productivity			1.00	0.29	0.60
factory size (N)				1.00	0.40
factory size (K)					1.00

Notes: Each variable is a vector of 18 observations, one for each industry in the sample. See Notes to **Table 2.2**.

2.3. REGULARITIES IN THE INDUSTRY WAGE STRUCTURE

Krueger and Summers (1987, p.26: Table 2.3) find that the median correlation coefficient of industry wage structures in UK, Canada, USA, Japan, France, Germany and Sweden, is in the neighbourhood of 0.85-0.90. In comparison, the industry wage structures of Bolivia and Mexico have a median correlation coefficient of about 0.5 with the wage structures of these OECD nations. The authors conclude that there is a strong common factor among IEs that LIEs do not share to as great an extent. Further, since the inter-country correlations in 1982 are stronger than in 1973, it seems that the process of development in these countries is bringing their wage structure closer to the pattern seen in the more industrialized nations. Implicit in this idea is the notion that the wage structure in LIEs is *less stable over time.*

This coincides with the findings of Papola and Bharadwaj (1970). However, **Table 2.5** shows that the industry wage structure in India was very stable through the 1980s. We have correlated industry differentials in India with the US industry differentials reported in Krueger and Summers (1987), Table 2.1, for the 16 industries that matched in classification[10]. The correlation coefficient is 0.60, which is significant at 2%. This figure for India is in the neighbourhood of corresponding figures for Bolivia (0.51) *and Norway*

Table 2.5
STABILITY OF THE INDUSTRY EARNINGS STRUCTURE OVER TIME

Year	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
1979	1.00	0.89	0.93	0.94	0.89	0.90	0.91	0.90	0.88	0.91	0.84
1980		1.00	0.97	0.98	0.98	0.97	0.97	0.97	0.96	0.98	0.94
1981			1.00	0.97	0.95	0.95	0.95	0.95	0.94	0.97	0.91
1982				1.00	0.97	0.95	0.95	0.96	0.94	0.96	0.92
1983					1.00	0.98	0.97	0.97	0.95	0.97	0.93
1984						1.00	0.95	0.96	0.95	0.95	0.90
1985							1.00	0.98	0.96	0.97	0.95
1986								1.00	0.97	0.99	0.94
1987									1.00	0.96	0.94
1988										1.00	0.95
1989											1.00

Notes: The figures are Spearman's rank correlation coefficients. Each is significant at 1%.

(0.67), and in general, a developing/developed country distinction does not seem to carry weight. Having established that India's industry wage structure shares some important features of industry wage structures in more developed countries, we now consider the significance of this result.

[10] Of the 18 industries in our sample, only Electricity and Wool & silk textiles found no counterpart in the US sample. We have imposed the following equivalences (format: *US industry=Indian industry*): Primary metals=Basic metals; Fabricated metals=Other metal products; Textile=Cotton textiles; Apparel=Textile products; Petroleum=Petroleum & rubber; Tobacco=Tobacco & beverages. The other 10 industries are exactly matched. The correlation coefficient on the sample of 10 where the matching is exact is 0.56, which is similar enough to the coefficient reported in the text.

Table 2.6 INDUSTRY WAGE DISPERSION IN SELECTED COUNTRIES			
Country	*s.d. of log wages*	*Country*	*s.d. of log wages*
Bolivia	0.168	Norway	0.107
Canada	0.239	Poland	0.097
France	0.126	Sweden	0.081
Germany	0.141	USSR	0.101
Japan	0.263	U.K.	0.140
Korea	0.314	USA	0.241
Mexico	0.155	Yugoslavia	0.120
		India	0.460

Source: Krueger and Summers (1987), Table 2.12. Row for India added from author's calculations.

There is now a fairly robust collection of evidence[11] on the existence of sizeable inter-industry wage differentials for similar workers performing similar jobs. Such differentials have been noted to be remarkably stable over time, across space, and across occupational groups. These properties of the data make it difficult to reconcile the differentials with competitive theories of the labour market. Long run industry wage differentials can only be incorporated in a competitive framework if they arise as a result of industry differences in unobserved attributes of jobs or workers. In the short to medium term however, industry wage dispersion may also arise as an expression of shifts in industry labour supply or demand that are associated with frictions such as imperfect labour mobility. However, the persistence of industry wage patterns over long periods of **time** makes it unlikely that *transitory* skill premia are primarily responsible for the wage differentials[12]. The competitive explanation of *long run* differences is further undermined by the fact that the industry wage structure is similar across **occupations**. If the unobserved ability of managers in a high-wage industry is high, there is no reason to expect that the unobserved ability of

[11] See Katz and Summers (1989), Krueger and Summers (1987, 1988), Dickens and Katz (1987) and Murphy and Topel (1987).

[12] Slichter (1950) and Krueger and Summers (1987) demonstrate the stability of the US industry wage structure over 1900-1984. Tarling and Wilkinson (1982) and Lawson (1982) describe the stability of industry wage differences in the U.K. Papola and Bharadwaj (1970) study data for 17 countries and find stable wage structures during 1948-65 in the industrialized countries in their sample.

manual workers in that industry will also be high. Moreover, the industry ranking of wages for a given occupational group does not change significantly when worker characteristics like education and age are held constant. Assuming that unobserved ability is correlated with observed worker characteristics, this makes it unlikely that industry wage differences reflect differences in unobserved ability. Furthermore, industry wage differentials exhibit fairly consistent correlations with *product market characteristics* like profitability, and competitive wage determination affords no scope for these to affect wages.

The industry wage structure is also remarkably similar across **countries**. This suggests that the wage structure reflects factors specific to the operation of industrial economies. In particular, industry wage differentials appear to transcend the institutional setting in a particular place or time. This is reinforced by the fact that the wage structure is similar for **union and nonunion** workers within a given country (Dickens and Katz, 1987). Also, in industries like steel and automobiles, where it is tempting to attribute high wages to union power, Katz and Summers (1989) demonstrate that substantial wage premia predate union organization. This is similar to the Mazumdar evidence for India (**Section 1.2**).

In conclusion, the regularities of the industry wage structure point to the significance of non-competitive forces in wage determination. These seem to be fundamentally associated with technological characteristics of industries, rather than with particular collective bargaining systems or government interventions in the labour market. The Indian evidence may thus be regarded as pointing to the importance of efficiency wages, although this does not rule out rent-sharing. In the next Part of this chapter, we estimate a model of wage determination that encompasses bargaining, efficiency wage and competitive mechanisms. These alternative theories of wage setting are not reviewed in any detail as there is an abundance of such reviews in the existing literature. For example, Katz (1986) and Akerlof and Yellen (1986) review efficiency wage theories and Lindbeck and Snower (1988) and Oswald (1985), respectively, survey insider-outsider and union models of wage determination.

PART 3: ESTIMATING EARNINGS FUNCTIONS ON PANEL DATA

We begin by developing a theoretical model of wage determination in **Section 3.1**, and in **Section 3.2**, the corresponding empirical specification is evolved, and the data and estimation issues discussed. Results are in **Section 3.3**.

3.1. A THEORETICAL MODEL

Firm-Level Wage Determination

In a sequence of papers, Nickell *et al* (Nickell and Wadhwani 1990b, Nickell and Kong 1992, and Nickell, Vainiomaki and Wadhwani 1994) have developed a wage *bargaining* model which shows that the bargained wage is a linear combination of the '*insider wage*' and the '*outsider wage*'. The insider wage is the quantity that would, on average, induce the firm to employ all the insiders and the outsider wage is that which would prevail if only conditions outside the firm mattered. The insider term is basically a measure of rent or of nominal productivity which is consistent with the intuitive notion that, allowing some worker power, firms which generate greater surpluses will pay higher wage premia. In fact, the weight attached to the insider wage (or the *insider weight*) is increasing in union power and in product market power.

In the standard efficiency wage model, wages are set by the *Solow condition* that the effort-wage elasticity equals one, and so only variables that influence worker effort will affect the level of the wage that is set. Incorporating a role for firm-specific variables is a simple matter. For instance, under the shirking hypothesis (Shapiro and Stiglitz, 1984), firms pay a wage premium to induce loyalty and discipline, given that monitoring workers' effort is difficult or costly. Since it is usually harder to monitor workers in big firms and the costs of shirking are greater where valuable equipment is involved, the wage elasticity of effort is very likely a function of *size* and *capital intensity*. Alternatively, if workers have notions of fairness (Akerlof, 1982), and if their aspirations rise in proportion with firm performance, then the efficiency wage will depend on *firm performance*.

Therefore, if we are looking to explain features of the industry wage structure, it is desirable to start with a model that explicitly incorporates both possibilities, namely that wages are set by a firm-union bargain, and that wages are set by firms who operate on efficiency wage considerations. Nickell and Wadhwani (1990b) have demonstrated that the wage outcome under bargaining is much the same as that under short-run monopsony[13] (eg Mortenson, 1970), which may be recast as an efficiency wage model of the turnover type (see Annexe 4.1, Layard, Nickell and Jackman (1991), p.541). In Annexe 3.1 (p.540, *ibid*), the authors introduce effort in the bargaining framework and solve for unemployment. The model that is set out here proceeds from there to solve for wages. Somewhat *novel features* of the model developed here are the distinction between observable and unobservable effort, the inclusion of size as an explicit variable, and the specifications of the wedge and the alternative income terms. Further modifications that arise as a response to the data or institutions in India are considered in the following discussion of the empirical model.

Let production (Y) depend not only on the factors, capital (K) and labour (L), but also on the effort (F) of workers. Then we can write:

$$Y = Y(F(.), N, K, A) \tag{1}$$

In our data, we have information on annual days actually worked, which represents a visible component of effort. We therefore decompose total effort as:

$$F = D\,(F/D) = ED \tag{2}$$

where *D is days worked per worker* or visible effort and F/D or *E is effort per day* or invisible effort. The invisible component is necessarily offered by workers, though it may be induced by employers. On the other hand, visible effort, as defined, may be jointly agreed or set by either party. It may also be exogenously determined, as in the case of days

[13] Monopsony is the situation in which the firm faces an upward sloping supply curve, implying that the marginal cost of labour exceeds the average cost. In order to recruit additional workers the firm has to raise its offered wage. This situation is consistent with a perfectly competitive model in a short run characterized by frictions and skill-rigidities, but is observationally equivalent to an imperfect competition situation.

lost due to power shortages. In general, if W is the wage[14] and z_d are other determinants of D that we take to be exogenous, then

$$D = D(W, z_d) \tag{3a}$$

Turning to unobserved effort, the basic efficiency wage hypothesis is that this is a function of the relative wage and unemployment (see Shapiro and Stiglitz, 1984). More generally, workers care about (a) their absolute standard of living, measured by their consumption wages, (b) their standards relative to some comparison group (for a discussion of reference group theory, see Argyle, 1987), and (c) their current standards relative to their past standards (on adaptation theory applied to pay, see Goodman, 1974). Unemployment (u) enters the effort function on the grounds that poorer job opportunities outside make the consequences of losing one's job look more grim, causing incumbent workers to exert more effort than otherwise. Thus:

$$E = E[(W/W^a), (W/W^a)_{-1}, (W/P^c), (W/P^c)_{-1}, u, \varsigma_i] \tag{3b}$$

where W is own wage and W^a is outside wage, both in Rupees, and P^c is a cost of living index. Firms care about the product wage (W/P) as the mark up is inversely related to this, while workers care about their purchasing power (W/P^c). The *price wedge* (P^c/P) drives these objectives apart, and the degree of wage pressure in the economy depends on the size of the wedge. ς_i is a *firm-specific effect* which is introduced to capture the notion that there are fixed 'structural' traits of a firm, associated with its technology, that contribute to determining effort levels. For example, small differences in effort may be more visible, requiring a relatively high level of effort, other things being equal. It is evident from (3b) that the efficiency wage is a function of outside opportunities and a fixed firm effect. On the basis of the discussion at the start of this section, we allow that the effort elasticity is

$$e_1=f(\pi, \text{size}) \tag{3c}$$

and then a measure of profits (π) enters the efficiency wage function irrespective of

[14] In this Section any reference to wages should be understood as reference to annual wages or earnings.

bargaining. We now move on to incorporate wage bargaining in the model.

Let the firm with the technology described by (1) and (2) engage in wage bargaining with its workers, who may be unionized. The process is taken to be resolved as a Nash bargain (Nash 1950, 1953)[15]. Denote U and π, respectively, as the union and firm objective functions, U^a and π^a as the fallback levels of utility and profit, and β as the relative bargaining power of workers. Then the agreed wage is chosen so as to maximize Ω, the *Nash maximand*, subject to the firm's employment decision:

$$\max_{W} \ \Omega = (U-U^a)^{\beta}(\pi-\pi^a) \tag{4a}$$

$$\text{subject to } \partial\pi/\partial N = 0 \tag{4b}$$

It is assumed here that the firm first sets or agrees upon the wage and then determines the optimal employment and price levels. As the involved parties are aware that profit maximization, or being positioned on the labour demand curve[16], entails an employment-wage trade-off, the wage decision is conditioned on the employment decision. We now proceed to specify the functions in equations (4a) and (4b). Let union utility be:

$$U= S(W/P^c) + (1-S)(A/P^c) \tag{5a}$$

where S=S(W) is the survival probability or the probability of the representative worker being employed in the same firm in the next period, and the elasticity $\varepsilon_{SW} < 0$. W is the nominal wage in the existing job, A is the wage available in the event of layoff and P^c is a cost of living index[17]. Assuming that the alternative income in the event of job loss is

[15] Binmore *et al* (1986) provide a strategic justification of this and Layard, Nickell and Jackman (1991), Annexe 2.2, pp. 534- 536 offer an intuitive discussion of bargaining theory.

[16] In fact, in the presence of efficiency wages, it is not possible to discriminate between efficient bargaining (optimum on contract curve) and right to manage (optimum on labour demand curve). See Layard, Nickell and Jackman (1991), Annexe 4.2, p.543.

[17] In principle, if effort responds to wage relativities referring both to the worker's past and to his or her reference group, then these factors should also count as increasing union utility. If such is the case, we should have a more general specification of U, including (a) the lagged wage and (b) the comparison wage which, as the model is written, enters the Nash maximand through U^a and not through U. However the form of the wage equation that emerges at the end is not sensitive to the simplification employed in constructing U.

equivalent to the fallback income available in the event of a strike, we have[18]:

$$A/P^c = U^a = (1-\phi(u))(W^a/P^c) \tag{5b}$$

where W^a=the expected fallback wage, u=the unemployment rate, ϕ reflects the probability that a displaced worker will not find employment elsewhere and $\phi'>0$. Given (5a) and (5b) we can write the union's contribution to the Nash maximand as:

$$U-U^a = S[W - (1-\phi(u))W^a]/P^c \tag{5c}$$

where, recall, S=S(W) and naturally, $\varepsilon_{SW}=\partial S/\partial W < 0$.

The firm's objective is assumed to be profit (π), and if all workers were to go on strike, its fallback income (π^a) would be the negative of its fixed costs, f. As usual, π=PY-WN-f, where P is the price of value added. Therefore $(\pi-\pi^a)$=PY-WN. Using (1) and (2) and denoting revenue by R, we can write this as:

$$(\pi-\pi^a) = R[K, A, NED] - WN \tag{6}$$

where it has been assumed, with little loss of generality, that effort is labour-augmenting. Using (5c) and (6), we can rewrite the maximization problem in (4) as:

$$\text{Max.}_W\ \Omega = \{S^\beta[(W/P^c) - (1-\phi(u))(W^a/P^c)]^\beta\}\ \{R[K, A, NED] - WN\} \tag{7a}$$

$$\text{s.t. } \partial\pi/\partial N = R_3ED - W = 0 \tag{7b}$$

where R_3 is the derivative of the revenue function with respect to its third argument and E and D refer to the effort and days functions defined in (3) above. Thus:

$$\partial\log\Omega/\partial W = (\beta/S)(\partial S/\partial W) + \beta/([W - (1-\phi(u))W^a]) + (1/\pi)\{R_3[N\partial(ED)/\partial W + ED\partial N/\partial W] - N - W\partial N/\partial W\} = 0, \text{ and so,} \tag{8a}$$

$$\partial\log\Omega/\partial\log W = \beta\varepsilon_{SW} + \beta W/([W - (1-\phi(u))W^a]) + (WN/\pi)[\varepsilon_{DW} + \varepsilon_{EW} - 1] = 0 \tag{8b}$$

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18 We do not entertain the possibility of unemployment benefits in specifying alternative income because there are none in India.

where ε_{SW} is the absolute elasticity of the survival probability with respect to the wage, $\varepsilon_{DW}=\partial logD/\partial logW$ and $\varepsilon_{EW}=\partial logE/\partial logW$. Define $Z=[\varepsilon_{DW} + \varepsilon_{EW}]$. Then on the basis of (3b) and (3c) we can write $Z=z(W, W^a, P^c, D, size, \pi)$. Since $\beta > 0$, $\varepsilon_{SW}>0$, the first two terms in (8b) are positive and it follows that $Z<1$. Therefore the elasticity of total (visible and invisible) effort with respect to the wage is less than unity[19]. While this violates the Solow condition, it is perfectly consistent with a framework in which efficiency wage and bargaining models are combined (see **Appendix 6.1**)[20].

At this point it is useful to introduce the demand curve facing the firm, which is assumed to be isoelastic:

$$Y = P^{-\eta}\Theta Y_{di} \tag{9}$$

where Y=value added output, P=the price of Y, η=demand elasticity, Y_{di}=a demand index and Θ=a random value that is revealed *ex post*. Using (1) and (9), profit-maximization gives the marginal revenue product condition, which can be solved for employment. As the basic mechanics of this step are set out in the model in **Chapter 4**, they are not detailed here. If (1) takes the constant returns Cobb-Douglas form then:

$$(N/K) = [1/ED)] \{(\Theta^{-\eta})[(WK^{1/\eta})/(\alpha\kappa Y_{di})]\}^{-1/(1-\alpha\kappa)} \tag{10a}$$

where α=labour share and $\kappa=1-1/\eta$ is an indicator of product market competition. If Θ is taken as having a unit mean, it can be shown that the maximized profit satisfies

$$\pi = [(1-\alpha\kappa)/\alpha\kappa]WN \tag{10b}$$

which implies that (WN/π) is a constant. To specify the survival function, we define the

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[19] Of course, concentrating on invisible effort, it is also the case that $\varepsilon_{EW}<1$.

[20] The comparative statics of the final wage equation in (12) are quite intuitive once the model has been followed through and so they will not be made explicit. However, since we have contributed D to the model, we now consider the likely sign on its coefficient. With reference to (8b), if π=PY-WN then $WN/\pi=[(PY/WN)-1]^{-1}$. Let the coefficient on p+y-n be λ. Then it is clear that the coefficient on log[Z-1]= -λ. Let $\partial logZ/\partial logD=\zeta$. Then the coefficient on logD will be $-\zeta\lambda$. But $\partial logZ/\partial logD = (1/Z)(\partial\varepsilon_{dw}/\partial logD)$. If the elasticity of days w.r.t. the wage declines as days worked increases, then this is negative. In that case, $-\zeta\lambda>0$, or days per worker has a positive impact on the wage.

insiders, or the employees who are party to the wage bargain, as $N^I = (1-\delta)\, N_{-1}$, where δ=the quit rate and N_{-1}=last period employment. Then survival depends on the number of insiders relative to expected employment, N(W), that is, $S = S(N^I/N(W))$, and so

$$\varepsilon_{SW}(W)=\varepsilon_{SN}\,[N^I/N(W)]\,\varepsilon_{NW} \tag{11}$$

where, from (10a), $\varepsilon_{NW} = 1/(1-\alpha\kappa)$, $\alpha\kappa$ is the labour share when firms are price-setters and the elasticities are in absolute terms. Using (10a), (10b) and (11) in (8b) and log-linearizing, we arrive at the wage equation:

$$\mathbf{w = \lambda\ [(p^e+y-n) + \gamma_1(n-n^I) + \gamma_2 days + \gamma_3 size] + (1-\lambda)\ [\gamma_4 w^a - \gamma_5 u + \gamma_6 p^c] + \gamma_7\beta} \tag{12}$$

where lowercase letters denote logs, w=own wage, p=expected industry price of value added, y=value added, n=employment, n^I=number of insiders, days=days worked per worker (so far referred to as *D*), size=average size of factory, w^a=the reference or outside wage facing the representative worker, u=unemployment rate, p^c=a cost of living index, β=index of union power, and λ is the insider weight. It can be demonstrated (Layard, Nickell and Jackman 1991, p.183, eq.9) that $0\leq\lambda<1$ and that λ=f(union power, product market power). We estimate a dynamic form of (12). A theoretical underpinning for wage dynamics arises from the adaptation hypothesis (eq.3b).

The first square bracket contains 'inside' or firm-specific variables. Similar wage equations that have been estimated for other countries typically do not include *days* and *size*. But different sized firms may have different productivities. And productivity per worker is a positive function of days worked per worker. Therefore controlling for these variables provides a cleaner estimate of λ than otherwise. The second bracket in eq. (12) contains externally determined variables that affect workers' outside opportunities and that serve as reference points in determining their utility and effort. The equation allows for both wage bargaining and efficiency wage mechanisms. It subsumes the pure efficiency wage case, wherein γ_7=0 and n^I is replaced by the number of job slots. On the other hand, if there is only bargaining or if both regimes are 'on', then we have the full form of equation (12).

The basic intuition attached to λ is that both product market rents and the quasi-rents associated with fixed capital are shared with workers. The sharing may be 'forced' on the firm by the relative strength of the union, when these terms enter as influences on the survival probability; or it may be motivated by efficiency wage considerations such as 'gift exchange' or stimulating worker morale. In the latter case, capital intensity may stand not only for potential quasi-rents, but also for the sensitivity of the production process to effort on the part of workers.

The Industry-Level Wage Equation

Aggregation of (12) over firms yields an industry wage equation. Previously firm-specific variables become industry-specific. Implicit in aggregation are the assumptions that firms have a constant returns to scale technology and that prices and wages are uniform across the industry. By implication, average factor products are also uniform within an industry.

3.2. THE EMPIRICAL WAGE EQUATION

3.2.1. Data and Variables

Sources and definitions are detailed in the **Data Appendix**. The data are a panel of 18 two-digit industry groups, disaggregated by their location in 15 states, with annual observations going from 1979 to 1987. They refer to that part of manufacturing that is in the factory sector. The '*wage*' is the wage bill divided by the number of workers, which is really per worker annual earnings (w_{ist}). Having employment in the denominator of the dependent variable can lead to measurement error biases on right hand side terms containing employment (eg., $(y\text{-}n)_{ist}$). This is dealt with by instrumenting any such terms. We concentrate on production *workers* and their wages in order to narrow the skill-range, as there are no more-detailed data on skills. *Productivity* ($\pi=p+(y-n)$) is nominal gross value added per employee. Using the ASI's value added data at current prices (p+y) circumvents the problem of finding value added prices. Some authors use *per-worker profits* instead of productivity. However, since (short run) profit is just value added less wages and the wage is the dependent variable, value added is evidently superior in econometric terms and no worse in terms of the information it carries. The number of *insiders* can be specified as $N^I=(1-\delta)N_{-1}$, where δ is the quit rate. In logarithms, $n^I = \theta_0 + n_{-1}$, where $\theta_0=\log(1-\delta)$ is absorbed by the equation intercept. Thus, $n\text{-}n^I$ is simply Δn[21].

An alternative specification of the insider bracket in (12) is also estimated. Using the Cobb-Douglas production function, we can write:

$$p+y-n - \gamma_1(n-n_{-1}) = p + (1-\alpha)(k-n) - \gamma_1(n-n_{-1}) + a \tag{13}$$

where α is the employment elasticity of output, 'a' is an index of technical progress[22], k is capital stock, and the rest of the notation is familiar. In the absence of data on value added prices at the industry-state level, the *industry price* (p_{it}) is measured by the Laspeyres (fixed weight; base=1970) index of wholesale prices or 'list prices' for the entire industry. These price data incorporate import prices and reflect price controls where relevant. Some sub-sectors in Indian manufacturing, such as cement and sugar, were subject to price controls, although the 1980s witnessed considerable price deregulation (eg., cement in 1982). The *capital stock* (k_{ist}) data are adjusted to get a measure of gross stock at replacement prices. As a measure of '*a*', a modified Solow index of *technical progress* (a_{ist} *or* tfp_{ist}) is computed (see **Data Appendix**).

Additional terms in the insider bracket in equation (12) are work intensity and size. Work intensity is average annual days worked per worker ($days_{ist}$), where a day refers to eight hours. In the absence of establishment data, size is measured as average factory size in the industry, either in terms of capital, $(k\text{-}fac)_{ist}$, or in terms of employees, $(n\text{-}fac)_{ist}$, where *fac* is the number of factories. Both of these measures are referred to as $size_{ist}$ and the choice between the two is left to the data. Although the size-wage effect is an empirical fact (see

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21 If it is allowed that bargainers are concerned not only with the employment of existing workers, but with some wider group, then this generalizes to $n^I = \theta_0 + \theta n_{-1} + (1-\theta)n^*$, where n^* is trend employment. This implies $n-n^I = \Delta n + (1-\theta)(n_{-1}-n^*)$. In practice, this form is also estimated.

22 The coefficient on the technical progress index *(a)* is not λ but $\lambda\alpha$ if technical progress is specified as labour-augmenting in the production function.

Section 1.2), size does not figure in most theoretical models because no good theory has been found to underpin it. We have incorporated it in our model by allowing the wage elasticity of effort to depend on size. An alternative justification is to allow the magnitude of the productivity effect on wages (λ) to depend on size, for example with size proxying union and product market power[23]. When allowing a 'slope effect' ($size_{ist}$.π_{ist}) it makes econometric sense to allow an 'intercept effect' ($size_{ist}$) as well. The advantage of this manner of introducing size is generality. Size now appears as an independent variable in the 'insider bracket' even under pure bargaining, that is, it does not require efficiency wages. Statistics indicative of *union power* (β) are available as either industry or state time series, not as industry-state series. In any case, these data are unreliable. Therefore a direct investigation of union effects is not undertaken in this study, though industry-state and time effects are expected to go some way towards controlling for any impact of unions on wages.

A *consumer price index* (p^c=cpi_{st}) for industrial workers is available by region. It appears in the theoretical model as it affects worker utility and hence effort. Given industry output price, a rise in the cost of living generates real wage resistance, as workers try to maintain their real incomes[24]. There are no data on employer or employee taxes, nor disaggregate data on import prices and import shares, which, if available, would be additional elements of the wedge between real labour costs to the firm and the disposable income of workers. The *alternative wage* (w^a) is proxied by the state average of earnings of factory production workers (w_{st}). This is likely to be a better measure of the alternative income of an industrial worker than is the countrywide average. This is one of the virtues of having industry data disaggregated by region. Although it would be useful to obtain the coefficient on the *unemployment rate* (u_t), this is not possible as there are no annual data on unemployment. In a country the size of India, it is clear that one would want an unemployment rate more

[23] Larger establishments have stronger unions (**Section 1.2**). Product market power and concentration are correlated at the industry-level. It is plausibe that the average size of a factory in a highly concentrated industry is large.

[24] Although the models that illustrate such an effect indicate that it is temporary, the evidence for OECD economies is that it is long-lasting, and therefore has the potential to alter the equilibrium of the economy (Layard, Nickell and Jackman 1991, p.210).

local than the aggregate rate. We therefore employ the following first-order approximation of the state unemployment rate *(u_{st})*:

$$u_{st} = \alpha_s + \beta_t + v_s t = f(\theta_{is}, \theta_t, \tau_s t) \tag{14}$$

Thus, the unemployment rate is decomposed into a fixed effect (α_s), time dummies (β_t) and state-specific trends ($v_s t$). Levels of dualism in India's labour market suggest that, in addition to a measure of slackness, *structural variables* such as the proportion of organized sector jobs in the region or the proportion of casual workers, may determine job-getting prospects. These variables may also be expected to be picked up by state intercepts and trends. As an alternative to (14), we consider the change in factory employment at the state level (Δn_{st}) as a proxy for u_{st}.

3.2.2. Estimation

The wage equation includes *fixed effects (θ_{is})* that allow the intercept to vary between cross-sectional units. This takes care of stable aspects of work force composition such as, possibly, gender and skill. *Industry trends ($\tau_i t$)* are included to allow for trends in these unobserved variables and *state trends ($\tau_s t$)* are permitted so as to control more accurately for unemployment. *Time dummies (θ_t)* pick up aggregate unemployment and wage effects on the local wage. Under the conviction that both parties to the wage transaction are only concerned with real values, *nominal homogeneity* is imposed in estimation. This can be done in more than one way, but we divide all nominal variables by the alternative wage (w_{st}). The dependent variable is thus transformed to a relative wage. Since wages are set in nominal terms, wage-setters form expectations of future prices. Any deviations between actual and expected prices will generate unanticipated changes in real wages. To allow for such effects, we include an *inflation surprise term* ($\Delta^2 cpi_{st}$) in the equation. Let the expectation of this period's price level depend on the level and the change in last period's prices in the following way: $cpi^e = cpi_{-1} + \Delta cpi_{-1}$. Then the expectational error is

$$(cpi - cpi^e) = \Delta cpi - \Delta cpi_{-1} = \Delta^2 cpi \tag{15}$$

where cpi is the consumer price index (P^c_{st}), the price that workers care about.

Though, for simplicity, (12) is written as a static equation, we estimate a general distributed lag model. The *lagged dependent variable* (w_{ist-1}) captures inertia effects that may arise on account of wage resistance, employment contracts of longer than a year's duration, or the lagged wage acting as a reference wage for wage-setters (see eq.3b). Lags of the explanatory variables will figure if there are delayed effects that have a different time path than pure wage adjustment. It is difficult to predict the nature of lagged effects associated with the stickinesses of imperfect competition, expectational adjustments and feedback mechanisms. Therefore the dynamic structure is left unrestricted.

Given a dynamic equation to be estimated on panel data, OLS-levels estimates of the lagged dependent variable (LDV) coefficient are bound to be biased (*upwards*) on account of a correlation between w_{ist-1} and the unobserved fixed effects in the residual, θ_{is}. The within groups (WG) estimator, which is the most often used alternative, purges the error of the fixed effects by transforming the equation to take deviations from time-means, and then performing OLS (Hsiao 1986, chapter 2). However, as our panel covers only a short time stretch (T=9), (*negative*) biases of order 1/T will mark the WG estimate of the LDV coefficient because the WG transformation induces a correlation of this order between the equation error and the subtracted time means[25] (Nickell, 1981). Consistent estimates of the LDV coefficient and other endogenous parameters can be had from a short panel by using the Anderson-Hsiao (1982) estimator. We use the GMM estimator developed by Arellano and Bond (1991), which resembles this in using instrumental variables (IV) on a first-differenced equation, but is more efficient as it employs all available orthogonality conditions. It gives unbiased and consistent estimates under the condition that the errors in the levels equation are serially uncorrelated, which is the same as that the errors in the differenced equation are free of second and higher order serial correlation. Tests of this null hypothesis are provided by the software (DPD, see Arellano and Bond, 1988b) used for GMM estimation. As an additional check on the validity of the instrument matrix, the Sargan test statistic for overidentifying restrictions is also computed. While the two-step

[25] (n_{ist-1} - $n_{is.-1}$) is correlated with (e_{ist} - $e_{is.}$), where $e_{is.} = (1/T)(e_{is1} + e_{is2} + .. + e_{iT})$ and e is the error. *Iff* T is large, then the correlation becomes negligibly small.

standard errors that can be seriously misleading in small samples like ours (Arellano and Bond, 1991 and Blundell and Bond, 1995). Therefore, we consistently report the one-step estimates, with standard errors adjusted for heteroskedasticity.

At first, all current-dated variables are treated as potentially *endogenous* because of the time aggregation implicit in annual data. This also takes care of the possibility that the timing assumptions on which the theoretical model is structured are not accurate. In any case, we would want to instrument labour productivity and the change in employment, as their realized values are substituted for their expected values, and the surprise terms are then consigned to the equation error. *Instruments* are second and further lags of the dependent variable and other endogenous explanatory variables. The empirical model in *levels* is thus:

$$(\mathbf{w}_{ist} - \mathbf{w}_{st}) = \theta_0 + \theta_{is} + \theta_t + \tau_i \mathbf{t} + \tau_s \mathbf{t} + \eta(\mathbf{w}_{ist-1} - \mathbf{w}_{st}) + \lambda[\ (\pi_{ist} - \mathbf{w}_{st}) + \nu_1 \Delta \mathbf{n}_{ist} + \nu_2 \mathbf{days}_{ist} + \nu_3 \mathbf{size}_{ist}\ ] + (1 - \lambda)\ [\nu_4(\mathbf{cpi}_{st} - \mathbf{w}_{st}) + \nu_5 \Delta^2 \mathbf{cpi}_{st}] + \mathbf{e}_{ist} \qquad (16)$$

where lowercase letters denote logs and subscripts i, s and t stand for industry, state and year respectively. θ_0=a constant intercept, θ_{is}=(N-1) industry-state fixed effects, θ_t=(T-1) time dummies, $\tau_i t$ and $\tau_s t$=industry and state trends, w=worker earnings, π=nominal value added per worker, n=employees, Δn=employment growth, which is a hysteresis term, days=days worked per worker, size=average number of employees per factory, though average capital per factory is used as an alternative, cpi=the general consumer price index for industrial workers, Δ^2cpi=an inflation surprise term and e=the equation error. All nominal variables are deflated by the average state wage (w_{st}). Second-order dynamics are included in estimation although these are not explicit in (16). An additional hysteresis term that is investigated is $(n_{ist-1}-n^*_{ist})$, where n^* is trend employment. We also experiment with inclusion of the change in factory employment in the state (Δn_{st}) as a direct proxy for unemployment. The coefficient on productivity, λ, is the *insider weight* and the first square bracket contains industry-specific terms. The larger is λ, the more flexible is the firm-level wage to firm performance, as opposed to external and labour market conditions. In the next section we discuss the results of estimating (16).

3.3. WAGE EQUATION ESTIMATES

Layout

The results are set out in **Tables 3.1-3.3. Table 3.1** presents estimates of a parsimonious form of (16), using four alternative estimators. The coefficients on the lagged dependent variable differ across the four equations in accordance with the theory. The OLS estimate is biased upward and the WG estimate is biased downwards. OLS on the first-differenced model (FD-OLS) also produces a strong downward bias. The IV estimate of the *productivity* coefficient (col.1, GMM) is larger than the OLS estimates in columns 2-4. This indicates that wage shocks cause opposing movements in wages and productivity. The same is true for work intensity (*days*), but the reverse for the cost of living (cpi_{st} or *consumer prices*). In **Table 3.2** we concentrate on GMM estimates. We start out with a second-order autoregressive wage equation (col.1). Since the time dummies are insignificant in col.(1), the equation is re-estimated without them (column 2). Column (3) reports the marginally altered estimates that result from dropping the second lag of the dependent variable. The coefficient on the first lag rises to compensate, and since we are short of degrees of freedom in the time dimension, (3) is preferred to (1). Admittedly, the downside is that second-order serial correlation in the differenced residuals becomes somewhat harder to reject. In columns 4 and 5, we include industry and state trends to account for any omitted variables that are well proxied by sector specific trends (eg, union power). Some variants of the basic model are reported in **Table 3.3**. These include the addition of a size-productivity interaction term, the specification of alternative insider variables (eq.13 above), investigation of outlier effects on the size coefficient, use of a statistical alternative to the measure of the outside wage, and definition of the dependent variable as the average wage rather than earnings.

General diagnostics

Most coefficients are well-determined and the estimated equation looks sensible. Although the second-step GMM estimates are better determined, we report the first-step GMM estimates as these are more reliable in finite samples (Arellano and Bond, 1991). The reported standard errors are robust to heteroskedasticity. The tables report a Wald test of the joint significance of all right hand side variables, which is consistently significant at 1%. The hypothesis of no second-order serial correlation in the residuals cannot be rejected at the 95% level. The Sargan statistic consistently indicates that the GMM instruments used are valid in the sense that they are not significantly correlated with the residual.

Overview

Robust effects flow from productivity, work intensity, size, the alternative wage and the cost of living. Thus both industry-specific and external variables count, and real wage resistance appears to have permanent effects. The Wald test on the joint significance of the insider or industry-specific variables is 80 ($\chi 2_3$). None of the distributed lag terms is significant. The hysteresis terms are also insignificant, and so are not reported. There is evidence of real wage inertia, though this is eradicated when industry-specific trends are included. The industry trends are highly significant, indicating that there are substantial industry differences in the wage path, even after variations in industry-specific productivity, size and work intensity are controlled for. This invisible industry variation may be on account of trends in skill or other aspects of technology and work force composition. If omitted worker and job characteristics are untrended, the industry trends may be interpreted as suggestive of non-competitive forces in wage determination. The time dummies are generally not significant, that is, aggregate factors (θ_t) appear not to have any strong independent effecton the wage, reinforcing our view of labour markets segmented along industry and state lines. We now consider the particular coefficients obtained, starting with the insider weight, on which most emphasis is laid. Unless otherwise specified, the coefficients discussed arise from the long run solution of eq. (3) in **Table 3.2**.

The 'insider weight' (λ)

The central result is that 'inside' productivity has a significant influence on the wage, though 'outside' or market factors modify the actual outcome. If the labour market were perfectly competitive, then the industry-state wage (wist) would simply track the outside wage (wst or wt). The long run *insider weight* is 0.21. In the wage equation estimated on regional data in **Chapter 2,** the elasticity of the wage (wst) with respect to productivity (πst)

WAGE EQUATIONS

Dependent variable=wage$_{ist}$

	TABLE 3.1: DIFFERENT ESTIMATORS				TABLE 3.2: GMM ESTIMATES				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variant/ Variable	**GMM**	**OD-OLS**	**FD-OLS**	**Levels-OLS**	*basic*	*drop τ_t*	*drop w_{t-2}*	*add $\lambda_i t$*	*add $\lambda_s t$*
constant	0.005 (1.0)	-0.03 (2.6)	-0.005 (0.6)	-2.0 (4.2)	**0.013 (0.7)**	0.003 (0.7)	0.004 (1.0)	0.011 (1.1)	0.019 (1.7)
wage$_{ist-1}$	0.18 (2.3)	0.11 (2.5)	-0.27 (10.1)	0.71 (21.0)	0.10 (1.2)	0.12 (1.5)	0.18 (2.3)	0.09 (1.2)	0.04 (0.5)
wage$_{ist-2}$					0.09 (2.0)	0.10 (2.0)			
outside wage$_{st}$	0.30	0.34	0.52	0.17	0.27	0.31	0.30	0.35	0.50
productivity$_{ist}$	0.17 (4.6)	0.10 (5.5)	0.07 (4.8)	0.10 (7.3)	0.17 (4.5)	0.17 (4.5)	0.17 (4.6)	0.16 (4.5)	0.15 (4.2)
days per worker$_{ist}$	0.41 (3.7)	0.37 (3.3)	0.25 (2.5)	0.33 (3.6)	0.37 (3.6)	0.35 (3.4)	0.41 (3.7)	0.36 (3.2)	0.34 (3.0)
factory size$_{ist}$	0.11 (5.2)	0.08 (4.0)	0.08 (4.5)	0.02 (3.8)	0.10 (4.7)	0.10 (4.9)	0.11 (5.2)	0.11 (5.1)	0.10 (4.8)
consumer prices$_{ist}$	0.35 (3.3)	0.45 (6.8)	0.68 (8.4)	0.02 (0.8)	0.37 (2.5)	0.30 (2.6)	0.35 (3.3)	0.40 (3.7)	0.31 (3.1)
time dummies	1.7/6(0.94)	13/7 (0.07)	36/7 (0.0)	29/7 (0.0)	1.7/6 (0.94)	n.a.	n.a.	n.a.	n.a.
industry trends					n.a.	n.a.	n.a.	40/17 (0.0)	37/17 (0.0)
state trends					n.a.	n.a.	n.a.	n.a.	16/14 (0.3)
serial corr(2)	1.7 (0.09)	1.8 (0.07)	-2.9 (0.0)	6.5 (0.0)	-0.16 (0.87)	-0.08 (0.94)	1.7 (0.09)	1.5 (0.14)	0.98 (0.33)
Sargan test	71/64 (0.26)	n.a.	n.a.	n.a.	63.4/62 (0.43)	61.6/62 (0.49)	71/64 (0.26)	66.3/64 (0.40)	61.5/64 (0.56)
NT	1831	1831	1831	2094	1568	1568	1831	1831	1831
σ^2	0.016	0.017	0.011	0.031	0.015	0.016	0.016	0.015	0.014
Wald (RHS)	112.2/5	144/5	191.1/5	3632/5	102.3/6	104/6	112.2/5	219.4/22	272/36

Notes: N=263, *serial corr*=serial correlation. The equation is estimated with the dependent variable specified as the relative wage. Its mean, in levels, is -0.13 and its standard deviation is 0.49. *Instruments* in equation (1): w(3,4), w_s(2,3), days(3,4), n(3,4), y(3,4), cpi(3,4), Δsize, time dummies and industry or state dummies, as applicable; where x(a,b) denotes xt-a,..,xt-b. See the **Data Appendix**.

was estimated as 0.45. The fact that we now get a much smaller coefficient underlines the importance of controlling for fixed effects when looking for the true impact of variables that show both cross-sectional and time variation. The new estimate of 0.21 is well-determined and robust to variations in the equation specification including the addition of time dummies and industry trends (compare col. 2 & 4 with col. 1. in Table 3.2). Industry trends are especially relevant because they are expected to control for industry differences in the evolution of average skill levels, which would otherwise tend to create an upward bias on the productivity coefficient. The evidence that wages adjust to changes in sector performance implies that employment is relatively stable[26]. The important implication is that gains from prosperity are not widely distributed. An interesting question is whether this is symmetric, that is, whether it is wages and not jobs that suffer the brunt of bad times.

Is the insider effect asymmetric?

Although this is not directly investigated here, India's employment record in the 1980s appears consistent with the hypothesis that the insider effect is asymmetric, that is, larger in good than in bad times. By this hypothesis, *growing* industries will have healthy wage growth and relatively slow growth in employment, while *shrinking* sectors will exhibit only a small slackening of wage growth and rapid downward adjustment of employment. So in a period of 'industrial turbulence' such as the 1980s in India, on average, one may expect to see healthy wage growth together with little growth in employment. And this is precisely what we see. **Tables 1** and **2** in **Chapter 4** paint the disaggregate picture. Industries like Chemicals that were gaining in value added share had rapid wage growth without a significant acceleration in employment, whereas in declining sectors like Cotton and Jute Textiles, employment seems to have borne most of the adjustment. Interesting in view of their being wholly and largely in the public sector, respectively, Electricity and Basic Metals were the only two declining sectors where wages and not employment suffered. This reinforces our understanding of public sector commitment to employment but it challenges the view that its management is disengaged from economic realities.

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[26] It might be argued that legislative constraints on employment provide the backdrop to wage 'flexibility'.

Estimating the insider gap

We started out with the observation that there are large inter-industry earnings differentials in Indian manufacturing (**Section 2.2**). Now we are in a position to consider the wedge driven through the industry wage structure by the operation of industry-specific effects. With reference to equation (3) in **Table 3.2**, let us define:

$$\Delta w1_{insider} = 0.21\Delta\pi_{it} + 0.50\Delta days_{it} + 0.13\Delta size_{it} \quad (17a)$$

$$\Delta w^{2}_{insider} = 0.21\Delta\pi_{it} \quad (17b)$$

where $\Delta x_{it}=x_{1987}-x_{1979}$. The 18 industries are ranked by $\Delta w^{1}_{insider}$, the wage change attributable to the identified industry-specific factors. The difference between the medians of the top and bottom quartiles is 17%, the *insider gap*[27]. Thus on account of industry-specific factors alone, we may expect to see pay differentials widen by 17%. The exercise is repeated with $w^{2}_{insider}$, which captures 'pure' performance effects, and the gap is 12%.

International comparisons of λ

Table 3.4 shows estimates of λ for a number of countries, of which China is the one developing country besides India. 'Labour markets' in China are incipient. Hay *et al* (1994) estimate a wage equation for Chinese firms over the period 1983-87, and attribute the insider effect to the 1980s reforms, which encouraged firms to create worker incentives. As for the virtual absence of insider effects in the Scandinavian nations, one would expect local productivity effects on wages to be weak in the presence of corporatist wage setting. The fact that the insider weight in Indian manufacturing is larger than in the UK and Germany is somewhat surprising. There are at least three reasons why this is so. For one, the relative labour abundance in India may be expected to have made inside forces weaker than in a more industrialized economy. Further, while in India there is no conclusive evidence of the effective strength of unions in the wage bargain, in the UK this is an established fact. Finally, the UK data refer to much larger firms than do the Indian data. For example, the

[27] This procedure in adapted from that followed by Nickell and Wadhwani (1990b). The *insider gap* for their firms is 18% (Period: 1972-82, large firms: 5000+ employees on average).

sample used by Nickell and Wadhwani (1990b) had average employment of 6046 in 1982 whereas more than 78% of Indian factories had less than 50 employees in 1986 (ASI, 1986). This is of relevance because, *ceteris paribus*, one may expect the insider weight to be larger in larger firms (eg., Brunello and Wadhwani, 1989). We now look to see if any evidence of this can be gleaned from our sample of industries.

Table 3.4 : Estimates of λ For Different Countries

Country	**λ**	**Source**
China	0.23	Hay *et al* (1994)
Japan (large firms)	0.33	Brunello & Wadhwani (1989)
USA	0.30	Holmlund & Zetterberg (1989)
India	*0.21*	*this study*
Germany	0.10	Holmlund & Zetterberg (1989)
UK	0.08-0.15	Nickell & Wadhwani (1990b)
Sweden	0.04	Holmlund & Zetterberg (1989)
Norway	0.03	Holmlund & Zetterberg (1989)
Finland	0.00	Holmlund & Zetterberg (1989)

Source: Except for the row on *India*, this Table is adapted from Layard, Nickell & Jackman (1991), p.188.

Size and industry-specific performance effects

A size-productivity interaction term is expected to take a positive sign but in fact, it gains a negative and insignificant coefficient (**Table 3.3**, equation 1). In a generalization of this investigation, we estimate industry-specific coefficients on productivity. This allows not only average size effects but also union and direct market structure effects to show up. With Chemicals as the base industry, the interaction terms are jointly insignificant, the Wald statistic being 21.81 (χ^2_{17}). However, the productivity coefficient on Food Processing is individually highly significant. To make sure that this is not corrupting the restricted estimate of λ, the equation is re-estimated allowing just this one interaction. There is no significant change in any of the estimated parameters and the 'average' λ for industries other than Food is 0.16.

Alternative insider variables

As shown in **Section 3.2**, the insider bracket can be rewritten in terms of capital intensity (k-n), total factor productivity (tfp) and industry price (p). The wage equation with these replacing nominal productivity is in col.2 of **Table 3.3.** The insider weight, the coefficient on *p* and *tfp*, is 0.19, which is not significantly different from estimates of this in **Table 3.2**[28]. Capital intensity (k-n) has a positive coefficient that, taking account of standard errors, is about $(1-\alpha)\lambda$ (see eq.13).

In conclusion, the insider weight (0.21) in India is robust and of considerable magnitude. Thus industry wages are flexible to industry performance. In the long run this signifies non-competitive labour markets. Although the fairness and turnover versions of efficiency wage theory are consistent with industry prosperity effects on wages, the standard efficiency wage models that obey the Solow condition (Solow, 1979) do not allow for such effects. Analogously, there are union models (eg. McDonald and Solow, 1981) which have no room for a performance-pay relationship. Thus the existence of such effects is not trivial even if one has accepted that there is imperfect competition in the labour market.

We now look at the other industry-specific variables, before turning to a consideration of the importance of external labour market conditions.

Hysteresis

Hysteresis effects do not require unions, and may be expected in general, in the absence of corporatist wage-setting. The idea is that bargainers can claim larger wage increases the smaller is the incumbent work force whose survival is to be ensured (Blanchard and Summers, 1986). The coefficient on the hysteresis term (Δn *or* $n_{-1}-n^*$) is therefore expected to be negative. We find that both terms are completely insignificant. This is a good sign as

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[28] We have restricted the coefficients on *p* and *tfp* to be equal as their point estimates were not significantly different in the unrestricted model. However, it bears mention that the point estimate on the price (p), which was treated as endogenous, was so poorly determined as to be insignificant. This may merely be indicating that lagged prices are not good instruments for current prices. However it may also be that the price data are very noisy for reasons described in **Section 3.2.2**.

it implies that adverse shocks do not have persistent effects on the economy. However when the hysteresis term (Δn) is interacted with industry dummies, the interaction terms are jointly significant. The evidence is consistent with the operation of hysteresis in the Food processing, Transport equipment and Petroleum & rubber sectors.

Work intensity

We first discuss the coefficient on work intensity and compute its *total* effect. We then point out the relevance of this estimate for our analysis of employment in **Chapter 4.**

Interpretation of the obtained coefficient: The coefficient on actual days worked per worker ($days_{ist}$) in the earnings equation is the sum of two effects. The first is a directly proportional increase in earnings, and the second is the effect of *days* on the wage per day ($wage_{ist}$). As $days_{ist}$ generates a coefficient of 0.50, it is clear that *days* has a negative impact on the *wage*. Since this appears counter-intuitive, we take a closer look at this variable. A *manday* is 8 hours. *Days* measures actual time worked per worker, averaging over and undertime. In our context, growth in *days* appears to reflect recuperation of losses in production time along with negotiated hours increases (see Notes in **Data Appendix**). Any situation where pay is not cut when days are lost can explain the observation that as less days are lost, the wage per day *falls*. Since work stoppages due to unanticipated power shortages are no fault of workers, this is a likely situation in which the described effect will arise[29]. The estimated parameter is consistent with there being a fair amount of undertime work, or with labour being '*hoarded*'. It is recognized that in the absence of any direct evidence, this is only speculative.

An alternative explanation of a coefficient of less than one on *days* invokes a measurement error argument in relation to heterogeneity in the workforce. There is evidence of increasing

[29] Indian industry has been severely constrained by inadequate infrastructure. There was increased public investment in power and other infrastructure in the 1980s (Table 2.3, **Chapter 5**), which is expected to have contributed to increases in days worked.

The extent to which undertime influences earnings depends on pay arrangements. Personal enquiries indicate that regular factory workers are paid by the week or the month, rather than the day.

casualization of the factory workforce in the period under study (see **Chapter 4**, Section 6.3). In principle, casual workers are included in the employment count of the ASI. However, while *days* worked by casual and regular workers are counted on an equal basis, the *number* of casual workers is likely to be undercounted in an annual survey as many do not stay through the year. To some extent, their numbers will also be consciously under-reported, where the firm seeks to evade the Contract Labour Law. So increasing casualization will spuriously increase the days worked per worker, other things being equal. At the same time, a composition effect will lower the wage per day, since casual workers are paid less than regulars. The effect of this will be to bias the *days* coefficient downwards.

The total work intensity effect : The total impact of $days_{ist}$ on earnings incorporates the *indirect* effect working through productivity. This is calculated using the production function estimates reported in **Chapter 5**. Let the estimated wage equation (col.3, **Table 3.2**) be summarized as: *earnings = 0.21(productivity) + 0.50(days) + C*, where C is a vector of other variables that are independent of days. Taking the total derivative of this equation gives: *d(earnings)/d(days) = 0.21[d(productivity)/d(days)] + 0.50*. The production function estimated on these data implies that d(productivity)/d(days) = 0.93. As this is not significantly different from unity, substituting this into the wage equation gives *d(earnings)/d(days) = 0.21 + 0.50 = 0.71*, or the *total* effect of work intensity on wages is 0.71, as against the partial effect of 0.50.

Relevance to the employment experience in Indian factories: Given that we instrument *days*, it seems fair to assume that the obtained coefficient is not heavily biased downwards. Then, of relevance to the analysis of employment in **Chapter 4**, these results establish that additional days are less expensive than additional workers. In the standard analysis, there is a trade-off between the overtime premia associated with increased time input per worker and the fixed cost associated with an increase in the number of workers (eg. Hamermesh, 1993). When, on average, there is no overtime premium associated with increased days, then they are unambiguously more desirable from the point of view of the employer. This is true *a fortiori* if additional days contribute more to production than do additional workers, other things being equal. This is plausible when the increase in days worked implies an increase in capacity utilization, of which we find evidence in **Chapter 5**[30].

Average factory size

A recapitulation of the theoretical underpinnings and the empirical specification of *size* may be in order. The first is often neglected by researchers, and the second is of concern because we have industry and not firm data. In **Section 3.1**, we have shown how a size effect on earnings may arise when efficiency wages are paid. In a bargaining model, the degree to which rents are shared with workers (λ) may be a function of establishment size. As argued earlier, investigation of a 'slope effect' justifies allowing an 'intercept' effect. If the size-wage effect is not log-linear at the firm level, then aggregation over firms will not, in general, be valid. As a result, some may regard the obtained size elasticity with skepticism. However, by controlling for fixed effects, we are looking at the *within*-group variation. Over time, within any industry-state, fluctuations in size composition are likely to be small. So linearization is locally valid. But as *between* variations in size are large (see **Table 9, Chapter 4**), we must allow for heterogeneous size coefficients. When this is done, the hypothesis that the slopes are all equal cannot be rejected at conventional significance levels. One glance at **Table 9** in **Chapter 4** establishes that Electricity is an outlier with regard to size. Since overfitting may reduce the power of the Wald test, we separately investigate whether the size coefficient is significantly different in the Electricity sector, and find that it is not (see **Table 3.3**, col.3).

Size is measured as capital stock per factory, $(\text{k-fac})_{ist}$ or as employees per factory, $(\text{n-fac})_{ist}$. The two variables emerge with very similar coefficients. Since it makes no odds, and it appears that $(\text{k-fac})_{ist}$ is not orthogonal to π_{ist}, we prefer $(\text{n-fac})_{ist}$, and henceforth refer to this as $size_{ist}$. The size-wage elasticity is 0.13. We investigated a quadratic term in size, but it

[30] It may seem that the work-intensity effect on earnings should really be interpreted as a productivity effect because the actual structural change is that workers and machines alike are being more fully utilized. However, we obtain a significant *days* effect, *controlling* for productivity. Therefore the correct interpretation of the days effect seems to be that *some but not all work stoppages are paid for*. In this case, when there are less work stoppages, the wage bill rises.

was not significant. The OLS estimate on size is only 0.02, indicating that it is negatively correlated with the fixed effects. Even at 0.13, the size effect is small. However, two considerations must be borne in mind when looking at this magnitude. First, size may be in competition with productivity. Second, by their nature, size effects are more likely to be prominent in a purely cross-sectional wage equation than in an equation which relies on time variation in cross-sectional variables. Indeed, most existing studies of the size-wage effect have been conducted using a cross-section. The decomposition of wage variation reported in **Part 4** confirms this suspicion.

The state of play outside

In a bargaining model, w_{st}, *the alternative wage* facing workers is the union's fallback income. In an efficiency wage model, the firm sets the wage not only to reward workers, but also with a view to creating incentives to recruit, retain and motivate them. In setting its wage offer, it exploits the fact that workers care about their relative wage (w_{ist}-w_{st}). Thus, under both scenarios the external pay structure influences industry-state wages. Outside earnings, w_{st}, enters the earnings equation with a long run coefficient of 0.37. So, the wage in a certain enterprise is moulded by what workers in other enterprises in the region earn. But this is far from the whole story. It was observed in **Section 2.2** that there are large variations in industry wages *within* any given state (**Table 2.1**), and the significance of the industry-specific variables just discussed reinforces this.

The change in factory employment, Δn_{st}, is insignificant. Unemployment effects are controlled by the fixed effects (τ_{is}), time dummies (τ_t) and state-specific trends ($\tau_s t$) (see eq. 14). The last are insignificant and are dropped. In the absence of annual data on unemployment rates, we cannot identify a direct unemployment effect in this equation. However, the fixed effects, θ_{is}, are recovered from the estimated equation and a weighted average of these, θ_s, is regressed on regional variables (**Table 4.4b**). The elasticity of θ_s with respect to u_s is -0.41. While this establishes that the fixed effects contribute to controlling for unemployment, our investigations in **Chapter 2** show that the elasticity that describes the effect of changes in unemployment on changes in wages is smaller (-0.16).

The cost of living

There is robust evidence of real wage resistance, which tends to raise the equilibrium rate of unemployment (Layard, Nickell and Jackman 1991, pp.209-10). The estimates imply that just less than half (0.43) of any increase in the cost of living (cpi_{st}) is compensated by increases in nominal earnings. However, the value-added price (p_{ist}), which is hidden in the nominal productivity term (π_{ist}), and the average state wage (w_{st}) are also affected by cpi_{st}. The estimated equation, (16), is

$$(w_{ist}- w_{st}) = \theta_0 + \theta_{is} + \theta_t + \tau_i t + \tau_s t + \eta(w_{ist-1}-w_{st}) + \lambda[(\pi_{ist}-w_{st}) + v_1\Delta n_{ist} + v_2 days_{ist} + v_3 size_{ist}] + (1 - \lambda) [v_4(cpi_{st}-w_{st}) + v_5\Delta^2 cpi_{st}] + e_{ist} \quad (16)$$

Taking the long run and averaging over industries, this implies

$$\Delta w_{st} = \lambda/(\lambda+v_4)\Delta p_{st} + v_4/(\lambda+v_4)\Delta cpi_{st} \quad (20)$$

where p_{st} is the industry average of the output price (p_{ist}) that is implicit in π_{ist}. The problem is that cpi_{st} affects the wage, w_{st}, directly as well as indirectly, via its impact on p_{st}. The indirect effect is smaller, the more open the economy. Since India remained a relatively closed economy in the period under consideration, this effect cannot be neglected and the *total* impact of cost of living increases on the wage is not identified by the estimated equation. In order to fully specify it, we would need to model the determination of the industry value-added price, which is fraught with difficulties as it entails estimation of a product demand curve that can be quite sensitive to variations in (unobserved) tastes.

A positive cost of living effect on earnings is consistent with our knowledge of the wage setting system in Indian factories. In particular, *'dearness allowances' (DA)* are built into the wage contracts of all permanent workers. Wage contracts may last from one to three years, but cost of living adjustments are made from year to year[31]. As the DA system is known to differ between industries, the equation was re-estimated allowing industry specific

[31] Lags of the CPI were investigated but emerged as insignificant.

coefficients on the *CPI*. In *Food processing*, the CPI has a small negative impact (-0.17), significantly different from that in other industries. Increases in the CPI, which mainly reflect food prices, will imply an increase in raw material costs for the Food industry. In other industries (barring Textiles), there is no reason to expect input prices and the CPI to move together. The other significant interaction is on *Electricity*, where wage resistance is positive but smaller (0.10). This is less easily explained. Electricity is government-owned and is one of the high-wage industries (**Table 2.3**). It may be argued that as Electricity workers regularly receive generous wage increments, their real wages are seldom threatened by cost of living increases and so they exhibit little real wage resistance.

Wage inertia

There is some evidence that *inflation surprises* ($\Delta^2 cpi_{st}$) induce changes in real wages, or that there is *nominal* inertia. Since wage contracts are written for longer than a year and dearness allowances do not imply price neutrality (except for the very lowest paid workers), this is not surprising. However, while the effect is non-negligible in size, it is only significant at 12%, and so is not reported. Both the first and the second lag of the wage (w_{ist-1}, w_{ist-2}) are significant and the sum of their coefficients is 0.19. The finding that there is a positive degree of *real*[32] wage inertia suggests that the real wage is not the ideal market clearing instrument. It is also consistent with the significance of cost of living adjustments. Real wage resistance can be reconciled with union wage bargaining if utility depends on both current and past income, and it emerges from an efficiency wage model if effort depends on current relative to past wages (eq.3b). However, the inertia coefficients become indistinguishable from zero when industry trends are included in the model. As any factor that causes real wages to be trended would give rise to the appearance of autocorrelation in the wage, the autocorrelation should be regarded with some suspicion.

Some Variants

These are presented in **Table 3.3**. *Column (1)* presents the equation with the size-

[32] Recall that nominal homogeneity was imposed in estimation.

productivity interaction and *Column (2)* presents the equation with the alternative insider

Table 3.3
WAGE EQUATIONS: SOME VARIANTS
Dependent variable=wage$_{ist}$

Equation:	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Variant/ Variable	***size*productivity***	***altve. insider terms***	***size*ELEC***	***w_{st} definition***	***DV=w/day***
constant	0.002 (0.23)	0.009 (1.4)	-0.0002 (0.02)	0.005 (0.1)	-0.00 (0.01)
wage$_{ist-1}$	0.17 (2.2)	0.08 (1.0)	0.16 (1.9)	0.16 (2.0)	0.38 (3.1)
wage$_{ist-2}$		0.08 (1.8)			
outside wage$_{st}$	0.15	0.33	0.24	0.19	0.62
[p+tfp]$_{ist}$		0.16 (4.5)			
[k-n]$_{ist}$		0.04 (1.9)			
productivity$_{ist}$	0.26 (3.2)		0.18 (4.8)	0.17 (5.3)	
days/worker$_{ist}$	0.43 (4.4)	0.40 (4.0)	0.40 (4.0)	0.42 (4.0)	-0.35 (2.5)
factory size$_{ist}$	0.15 (3.5)		0.11 (4.5)	0.12 (5.8)	
consumer prices$_{ist}$	0.42 (3.0)	0.35 (2.8)	0.42 (2.9)	0.48 (3.6)	
size$_{ist}$*productivity$_{ist}$	-0.02 (1.5)				
size$_{ist}$*ELEC			-0.009 (0.2)		
time dummies	4.2/7 (0.76)	6.8/6 (0.34)	4.2/7 (0.76)	6.3/7 (0.51)	11.2/7 (0.13)
NT	1831	1568	1831	1831	1831
serial corr(2)	2.2 (0.03)	-0.11 (0.92)	1.9 (0.06)	1.7 (0.09)	3.4 (0.001)
Sargan test	85.2/84 (0.44)	73.8/72 (0.42)	65.8/64 (0.41)	72.9/64 (0.21)	33.7/33 (0.43)
Wald (insider)	65.7/4 (0.0)	39.9/3 (0.0)		60.4/3 (0.0)	
σ^2	0.016	0.017	0.016	0.017	0.026
Wald (RHS)	105.9/6	85.7/6	115/6	139.6/5	24.1/2

Notes: See notes to **Table 3.1**. *Instruments* are w(3,4), w_s(2,3), days(3,4), n(3,4), y(3,4), [cpi-w_s](3,4), size(3,4), τ_t; and where relevant, [size*y-n](3,4), k(3,4) and [p+tfp](3,4).

terms. *Column (3)* investigates whether the size effect is driven by Electricity. The central results have already been discussed and there are no significant changes in the other equation parameters. *Column (4)* uses $w^1_{st}=\Sigma_i(N_{ist}/N_{st})w_{ist}$, instead of $w^2_{st}=\ln[\Sigma_i(N_{ist}/N_{st})W_{ist}]$, where lowercase letters denote logs. The latter is the more natural definition of the average state wage and is used in all other equations. Under the decomposition exercise (see **Section 4.1**), the state-time averages of w_{ist} and w_{st} are equal only if w_{st} is w_{st}^{1}. But comparing col. 3 in **Table 3.2** with col. 4 in **Table 3.3**, it is clear that the altered alternative wage definition does not make a great difference, suggesting that the approximation is reasonable. In *Column (5)*, we investigate the relation between the day wage rate and work intensity, holding constant only aggregate factors. The purpose of this is to investigate the hypothesis proposed by Nickell and Nicolitsas (1994), that these two variables are inversely related. The underlying idea is that, if the industry is doing well, then if workers can bargain a higher wage, they can also bargain lower effort levels, assuming that effort causes disutility. This hypothesis is borne out in our results.

PART 4: DECOMPOSITION OF THE VARIATION IN WAGES BY INDUSTRY, STATE AND YEAR

In this Part, we use the estimated wage equation (col.3, **Table 3.2**) to decompose the cross-sectional and time variation in wages into fractions attributable to each of the observed 'inside' and 'outside' variables, and the unobserved variables encapsulated in the fixed effects. **Section 4.1** elaborates the method and **4.2** discusses the results, which are in **Tables 4.1a-4.3b**.

4.1. METHOD

The method of reclaiming the fixed effects from estimates of a first-differenced equation is set out for two cases; when composition effects are allowed, and when they are held constant, the difference being in the weights used.

4.1.1. Computing the Fixed Effects

Written in levels, the estimated earnings equation is:

$$w_{ist} - w_{st} = \beta_1 (w_{ist-1} - w_{st}) + \beta_2 \, days_{ist} + \beta_3 \, size_{ist} + \beta_4(\pi_{ist} - w_{st}) + \beta_5(cpi_{st} - w_{st}) + \tau_{is} + \tau_t + \lambda_i t + \varepsilon_{ist} \qquad (19)$$

where i=industry subscript, s=state subscript, t=year subscript, w=earnings per worker, days=days worked per worker, size=average number of employees per factory, π=nominal labour productivity, cpi=cost of living index for industrial workers, τ_{is}=industry-state fixed effects, τ_t=the cumulated year dummies, $\lambda_i t$=industry trends, ε=a stochastic error.

Industry fixed effects

Taking the long run and averaging over time in (19) gives:

$$w_{is.} - w_{s.} = \beta_1 (w_{is.} - w_{s.}) + \beta_2 \, days_{is.} + \beta_3 \, size_{is.} + \beta_4(\pi_{is.} - w_{s.}) + \beta_5(cpi_{s.} - w_{s.}) + \tau_{is} + c + \lambda_i c \qquad (20)$$

where c denotes a generic constant and $x_{is.}$ and $x_{s.}$ denote time averages of x_{ist} and x_{st} respectively. The error, ε_{ist}, averages to zero. We next average over states. Two possibilities arise here. One is to allow for location effects and the other, to hold them constant. Location is held constant using weights $N_s/N_.$. Here N_s and $N_.$ denote total employment in the state and India respectively, both averaged over the period under consideration. This gives:

$$(1-\beta_1)\ w_{i.} = \beta_2\ days_{i.} + \beta_3\ size_{i.} + \beta_4\ \pi_{i.} + \tau_{i.} + c + \lambda_i c \tag{21a}$$

where the state-specific terms ($\Sigma_s\ [N_s/N]x_{s.}$; $x=cpi_{s.}$, $w_{s.}$) have been absorbed by the constant, c. We can then obtain the *industry fixed effects* as:

$$\tau_{i.} = (1-\beta_1)\ w_{i.} - \beta_2\ days_{i.} - \beta_3\ size_{i.} - \beta_4\pi_{i.} \tag{21b}$$

where $\tau_{i.}$ now incorporates λ_i and the constants, c.

To allow for the fact that the different industries have different geographic distributions, we average (20) over states using employment weights N_{is}/N_i and, as above, transform to get the fixed effects as :

$$\tau_{i.} = (1-\beta_1)\ w_{i.} - (1-\beta_1-\beta_4-\beta_5)\ ws_{i.} - \beta_2\ days_{i.} - \beta_3\ size_{i.} - \beta_4\pi_{i.} - \beta_5\ cpi_{i.} \tag{22}$$

where as before, $\tau_{i.}$ incorporates λ_i and c. Now, however, $x_{i.}$ denotes $\Sigma_s\ (N_{is}/N_i)x_{is.}$ or $\Sigma_s(N_{is}/N_i)w_{s.}$, as the case may be. Also ws_i denotes $\Sigma_s(N_{is}/N_i)w_{s.}$, so as to distinguish it from $w_i=\Sigma_s\ (N_{is}/N_i)w_{is.}$. Notice that, on taking the weighted average of a state-specific variable (cpi_s and w_s), we get an industry variable rather than a constant. The reason is that industries differ in their geographic distribution[33].

State fixed effects

Following a similar procedure to that outlined above, and using weights N_i/N to average (20) over industries, gives:

[33] In **Table 4.1a**, $ws_{i.}$ is referred to as the *outside wage*. For each industry, $ws_{i.}$ is a weighted average of state wages, where the weights are the employment shares of that industry in each state. It has basically the same interpretation in the industry wage (w_i) equation, (23), as the alternative wage, w_{st}, has in the estimated wage (w_{ist}) equation.

$$(1-\beta_1)wi_{s.} = (1-\beta_1-\beta_4-\beta_5)\, w_{s.} + \beta_2\, days_{s.} + \beta_3\, size_{s.} + \beta_4\, \pi_{s.} + \beta_5\, cpi_{s.} + \tau_s + c + \lambda_s c \quad (23a)$$

where $wi_{s.}=\Sigma_i(N_i/N)w_{is.}$, is the (hypothetical) average state wage that would prevail if every state had the same industrial composition and $w_{s.}=\Sigma_i(N_i/N)w_{s.}$ is the actual state wage just as it appears in (20). This is called the outside wage in **Table 4.2b.** Like $w_{s.}$, $cpi_{s.}$ is unaffected by weighting. For the other variables, $x_{s.}=\Sigma_i\,(N_i/N)x_{is.}$. Transforming (23a) gives the state fixed effects:

$$\tau_s = (1-\beta_1)wi_{s.} - (1-\beta_1-\beta_4-\beta_5)\, w_{s.} - \beta_2\, days_{s.} - \beta_3\, size_{s.} - \beta_4\, \pi_{s.} - \beta_5\, cpi_{s.} \quad (23b)$$

where τ_s has incorporated λ_s and c.

Allowing for the fact that industrial composition varies across states by using the weights N_{is}/N_s, we get the fixed effects:

$$\tau_s = (\beta_4 + \beta_5)w_{s.} - \beta_2\, days_{s.} - \beta_3\, size_{s.} - \beta_4\, \pi_{s.} - \beta_5\, cpi_{s.} \quad (24)$$

where $\Sigma_s\,(N_{is}/N_s)w_{is.} = \Sigma_s\,(N_{is}/N_s)w_{s.}$. Note that this equality only holds because w_{st} is defined as a weighted average of log W_{ist}, rather than more naturally, as a weighted average of W_{ist} that is subsequently logged. Comparing equation (4) in **Table 3.3** with its counterpart, equation (3) in **Table 3.2**, demonstrated that this approximation is reasonable. The notation $x_{s.}$ here, denotes $\Sigma_s\,(N_{is}/N_s)x_{is}$ or $\Sigma_s\,(N_{is}/N_s)x_i$.

Year fixed effects

A similar procedure is followed to get year-specific effects. Averaging (19) over industry and state using weights N_{is}/N, we get:

$$0 = \beta_2\, days_{t.} + \beta_3\, size_{t.} + \beta_4\, \pi_{t.} + \beta_5\, cpi_t - (\beta_4 + \beta_5)w_t + c + \tau_t + \lambda_t c \quad (25a)$$

Transforming gives us the year-specific effects,

$$\tau_t = (\beta_4 + \beta_5)w_{t.} - \beta_2\, days_{t.} - \beta_3\, size_{t.} - \beta_4\, \pi_{t.} - \beta_5\, cpi_{t.} \quad (25b)$$

where τ_t includes λ_t and the constants c.

Since it is natural to expect that most of the variation in the nominal wage will be on account of consumer price inflation (Δcpi_t), the decomposition is repeated for *real wages.*

In this case, (25a) is transformed to give

$$\tau_t = (\beta_4 + \beta_5)(w\text{-}cpi)_{t.} - \beta_2\ days_{t.} - \beta_3\ size_{t.} - \beta_4(\pi\text{-}cpi)_{t.} \qquad (25c)$$

where all variables are in real terms.

4.1.2. The Decomposition of Wage Variation

The data are logged and then averaged. Bearing in mind that these will differ between the variable and constant composition cases, let the generic averaged variables be x_i, x_s and x_t for the industry, state and year equations respectively. The all-India manufacturing average for every relevant variable is obtained, using weights N_i/N, N_s/N and $(1/T)$ respectively, where T is the number of years. Let these grand averages be called *a*. Denote the deviations of the variables from their grand averages as $dx_i=x_i-a$, $dx_s=x_s-a$ and $dx_t=x_t-a$. The percentage variation of the wage in any unit from the mean wage can be expressed as *[exp(dw)-1]*100*. Call this quantity *wvarn*. We are interested in decomposing this into the variation explained by each explanatory variable, and by the unidentified (unobserved) fixed effects. This is got for each variable x_k, as $[(\beta_k dx_k)/dw)]*wvarn$. Once obtained by the procedure described above, the fixed effects are treated just like any other variable. Therefore, by construction, $\sum_k [(\beta_k dx_k)/dw)]*wvarn = wvarn$. In other words, the decomposition is exact.

4.2. RESULTS: A THREE-WAY DECOMPOSITION OF WAGE VARIATION

The results of the decomposition exercises are presented in **Tables 4.1a-4.3b**. The industry and state variation in wages is decomposed twice, once with the natural employment weights that pick up actual compositional differences (**Tables 4.1a, 4.2a**), and once with weights that are constructed to nullify compositional effects (**Tables 4.1b, 4.2b**). The time variation is also decomposed twice, once for the standard case where we are explaining nominal wage growth, and again by transforming the equation to absorb the *CPI*, so as to explain real wage growth (**Tables 4.3a, 4.3b**). In perusing the Tables, note that all figures are percentage deviations so that numbers that are below average are negative. The striking result is that the fixed effects account for the major part of the cross-sectional variation in wages, be this across industry or state, while most of the time-variation in wages is explained by the identified variables, namely productivity, work intensity, size, external pay rates and the cost of living.

4.2.1. THE INTER-INDUSTRY WAGE STRUCTURE

Refer **Tables 4.1a** and **4.1b**, where industries are ranked in ascending order of average nominal earnings over the period, 1979-87. Column (1) presents the percentage deviation of industry earnings from the manufacturing average. This is decomposed into the percentage deviation attributable to each of the observed explanatory variables and that contributed by the unobserved fixed effects. When the geographic distribution of industries is held constant (**Table 4.1b**), then the outside wage and the cost of living, which were initially state specific variables, fall out of the decomposition (see **Section 4.1**).

The regional *cost of living* (CPI) plays an insignificant role, which is not surprising as most industries are fairly widely dispersed and the effect seen here only reflects CPI differentials between industries caused by their location. For the same reason, the *alternative wage* generally has little explanatory power. However there are a couple of interesting exceptions. Tobacco & beverages pays the lowest wages in manufacturing, and it appears that this is not unrelated to the fact that about 60% of its employees are located in Andhra Pradesh, which, on average, pays the lowest wages in India. At the other end of the spectrum, high wage premia in Basic Metals are strengthened by the fact that most of this industry is located in Bihar, where mining and heavy industries are concentrated and unions are fierce. Yet, in sum, the *'outside'* variables do not hold much explanatory power. However, the industry-specific or *'inside'* variables account for a fair proportion of inter-industry variation in earnings (**Tables 4.1a** and **4.1b**). *Productivity* is an important factor underlying the wage supremacy of the petrochemical and machinery sectors, and also contributes to the low wages paid in agri-based sectors. This is true even when location is held constant, so it may be regarded as a pure industry effect. *Days worked per worker* can explain as much as a fourth of the total deviation of Food and Electricity wages from the mean and is non-

TABLE 4.1a
HOW MUCH OF THE INDUSTRY WAGE DIFFERENTIAL DOES THE ESTIMATED EQUATION EXPLAIN ?
Industries have different location-mixes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry	**Wage differential**	**Outside wage**	**Cost of living**	**Productivity**	**Days/wker**	**Size**	**Fixed effect**
Tobacco & beverages	**-63.28**	- 5.29	0.37	-15.06	- 3.70	- 7.50	**-32.10**
Food products	**-48.00**	- 1.54	0.20	- 7.70	-13.86	- 6.80	**-18.31**
Wood & furniture	**-41.81**	- 0.87	0.05	- 9.78	- 0.81	-21.04	**- 9.36**
Textile products	**-31.76**	0.69	0.48	- 4.50	0.12	-13.64	**-14.92**
Cement, glass etc	**-22.48**	0.06	-0.09	- 1.52	- 2.14	-10.54	**- 8.25**
Leather & fur	**-13.74**	- 0.07	-0.38	- 4.33	0.69	- 7.23	**- 2.41**
Metal products	**4.38**	1.98	-0.09	2.40	0.64	-20.20	**19.64**
Wool & silk textiles	**9.99**	1.75	0.18	3.76	5.26	- 5.89	**4.93**
Cotton textiles	**11.89**	0.83	0.28	- 7.45	2.81	2.59	**12.82**
Miscelleneous	**14.58**	1.82	0.10	5.93	1.60	-16.38	**21.50**
Paper & publishing	**20.06**	0.79	0.02	2.58	4.52	-10.58	**22.72**
Petroleum & rubber	**25.44**	2.22	-0.49	21.34	2.68	-15.23	**14.92**
Chemical products	**35.18**	0.93	0.11	18.78	4.61	- 6.40	**17.16**
Non-Elec machinery	**36.42**	1.66	-0.07	9.81	2.63	-11.99	**34.38**
Electricity generation	**46.28**	0.00	0.12	11.81	13.92	70.68	**-50.25**
Basic metals	**51.76**	3.57	-1.51	9.57	8.83	- 1.38	**32.68**
Electrical machinery	**54.08**	1.14	0.35	14.33	5.75	- 4.25	**36.76**
Transport equipment	**63.03**	2.79	-0.73	5.13	4.67	8.64	**42.52**
Manufacturing	**0.00**	0.00	0.00	0.00	0.00	0.00	**0.00**

Notes: See Section 4.1. The log s.d. in (1) is 0.46 and in (7) is 0.23.

TABLE 4.1b
HOW MUCH OF THE INDUSTRY WAGE DIFFERENTIAL DOES THE ESTIMATED EQUATION EXPLAIN?
The geographic distribution of industries is held constant

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Industry	**Nominal wage differential**	**Productivity**	**Days/ worker**	**Size of factory**	**Explained variation**	**Fixed effect**
Tobacco & beverages	**-42.16**	- 6.71	- 1.96	- 7.68	-16.35	**-25.82**
Food products	**-45.03**	- 7.56	-11.65	- 6.94	-26.15	**-18.87**
Wood & furniture	**-42.08**	-10.21	- 0.53	-20.22	-30.96	**-11.13**
Textile products	**-34.56**	- 5.59	- 0.61	-12.27	-18.47	**-16.08**
Cement, glass etc	**-18.43**	- 1.54	- 1.92	- 9.68	-13.14	**- 5.28**
Leather & fur	**-17.59**	- 6.37	0.29	- 8.91	-14.99	**- 2.60**
Metal Products	**- 7.41**	- 0.09	- 0.11	-18.83	-19.03	**11.63**
Wool & silk textiles	**6.09**	- 2.28	4.11	-4.32	- 2.49	**8.58**
Cotton textiles	**5.25**	- 8.95	2.07	3.55	- 3.33	**8.59**
Miscelleneous	**0.14**	2.55	0.85	-14.92	-11.52	**11.67**
Paper & publishing	**15.55**	0.75	3.60	-10.10	- 5.75	**21.30**
Petroleum & rubber	**11.48**	17.16	0.73	-14.17	3.72	**7.76**
Chemical products	**33.99**	17.37	3.48	- 5.78	15.07	**18.92**
Non-elec machinery	**33.87**	8.66	2.20	-10.70	0.16	**33.72**
Electricity	**47.77**	14.15	13.41	68.46	96.02	**-48.26**
Basic metals	**27.16**	7.70	4.16	- 5.47	6.39	**20.77**
Electrical machinery	**45.37**	12.53	4.50	- 3.48	13.55	**31.83**
Transport equipment	**52.73**	1.42	4.15	6.92	12.49	**40.24**

Notes: Composition is held constant by using weights N_s/N. See Section 4.1. The log s.d in (1) is 0.36 and in (6) is 0.20.

negligible in a number of other industries. *Size* explains a substantial proportion of the industry variation, and makes its dramatic contribution through Electricity. As this is an outlier in the size distribution that pushes up the average, the size variable appears to tug the wage below average in most other industries.

The role played by the *fixed effects* is the most prominent. In the majority of industries (14 in 18), they explain more than half of the total wage variation. In fact, in sectors with a positive wage differential, they account for virtually all of the variation, especially when location is constant (**Table 4.1b**). In some cases, the fixed effect is large enough to cause a *mean reversal*, that is, an industry which would otherwise have wages below average, has wages above the average on account of the fixed effects alone. This is the case, for example, in Cotton textiles. So the estimated wage equation leaves a large residual in explaining the inter-industry variation in wages. Now consider some properties of the residual distribution. How much tighter is it, and is the industry ranking altered? Dispersion in the fixed effects is about half that in earnings, and the industry ranking is much the same. The correlation coefficient between the fixed effects and earnings is 0.63, which is significant at 1%. Electricity has noticeably jumped rank. If Electricity is removed, the correlation is 0.97. These numbers are for the variable location case. When location is constant, the correlation coefficients are 0.54 (significant at 2%) and 0.96 respectively.

The dominance of the fixed effects may be seen as supporting the hypothesis put forward by Krueger and Summers (1987) and Dickens and Katz (1987) that the variance of industry wages cannot be accounted for by standard competitive factors. Skeptics may argue that the fixed effects represent unobserved worker and job quality factors that are not captured by industry output per worker. The data refer to production workers only, which limits worker quality differentials between industries to some degree, though of course they may still be large. However, the industry fixed effects account for, on average, 70% of inter-industry wage variation, which seems too large a fraction to be explained by worker or job characteristics that are uncorrelated with observed output per worker, holding constant factory size and work intensity. Finally, while it is a shortcoming of this analysis that there are no micro-level controls, it is an advantage that we have used panel data and controlled for productivity, size *and other* relevant effects, using the *correct* coefficients.

What factors underlie the industry fixed effects?

Time-invariant industry variables that impact on the wage include stable aspects of the workforce composition such as, possibly, the skill or sex-composition, though we have suggested that these are unlikely to have a very large weight. Long run industry differences in the role and power of unions are consistent with long run differences in industry wages. They may also reflect historical wage setting norms specific to industries (eg, as proposed by the Wage Boards), and ownership (public/private/ foreign). Alternatively, fixed technological differences between industries (ς_i in equation 3b, **Section 3.1**) imply different effort-wage elasticities and so, different optimal wage rates. Therefore permanent industry effects on wages are consistent with both the payment of efficiency wages and with 'institutional' effects on wages. Although, as pointed out in **Section 3.1**, these two models are not mutually exclusive, the industry ranking of the fixed effects appears to favour the first over the second. Unfortunately, we cannot investigate these possibilities as either the required data are unavailable, or the variables are inherently difficult to quantify.

4.2.2. THE INTER-STATE WAGE STRUCTURE

As described in the preceding section, the estimated wage equation (w_{ist}) is averaged to yield a state wage equation (w_s), and the variance in state wages is then decomposed into that attributable to the included variables and that which is consigned to the state fixed effects (**Table 4.2a-4.2b**). In both Tables, the states appear in ascending order of *actual* (variable composition) earnings.

The regional *cost of living* generally explains only a small part of the earnings variation and it contributes to slimming the distribution since the cost of living in the high-wage Eastern states of Orissa, Bihar and West Bengal is relatively low. The *outside wage*[34] and the own wage are one and the same when the estimated equation is averaged over industries using the 'correct' weights (**Table 4.2a**). However when industry composition is held constant across states (**Table 4.2b**), the outside wage persists as an explanatory variable. As may be expected, it plays a significant role at the two ends of the *actual* wage spectrum. For example, in Kerala, the average actual wage (col.3) is below the India average on account of industrial composition and this exercises a drag on Kerala's wage differential of -11%. It is inspite of this that, as column 1 shows, Kerala's wage *would be 25% above* the average, were its industrial composition identical to the average composition in India.

Both Tables indicate that industry-specific or inside variables dominate outside variables in an explanation of earnings variation. There are significant *productivity* differentials between states, so that even though the productivity coefficient is just 0.21, they translate into fairly large effects that account for about a fourth of the total variation. It is of particular interest that there are substantial inter-state productivity differences even when industrial composition is constant across states (**Table 4.2b**). Looking across states, it appears that the productivity effect on state wages has more to do with 'structural' or fixed state features than with the education of workers. Once again Kerala makes the point strikingly. Its literacy rate is close to 100% against Bihar's which is less than 50% and yet Kerala's productivity is well below average and Bihar's well above (see **Table 4.2b**). Human capital explanations of the wage distribution are set back by observations of this sort[35].

Days worked per worker also vary a lot between states, and contribute anywhere between a fifth

[34] Annual *earnings* is referred to as *wages* because it is familiar usage.

[35] Inter-state productivity differentials are investigated in Section 1.5, **Chapter 5**.

TABLE 4.2a

HOW MUCH OF THE STATE WAGE DIFFERENTIAL DOES THE ESTIMATED EQUATION EXPLAIN ?

States differ in their industrial composition

State	(1) Nominal wage differential	(2) Cost of living	(3) Productivity	(4) Days per worker	(5) Size of factory	(6) Explained variation (2+3+4+5)	(7) Fixed effect
Andhra	-48.85	0.57	-14.74	- 5.42	- 8.13	-27.72	-21.13
Kerala	-33.38	0.56	- 7.46	-14.38	- 0.56	-21.85	-11.54
Punjab	-16.34	-0.29	- 0.19	3.18	- 1.52	1.18	-17.52
Uttar Pradesh	- 9.10	1.22	- 5.01	- 5.71	10.36	0.87	- 9.97
Tamil Nadu	- 6.18	1.38	1.75	- 5.51	- 4.46	- 6.85	0.67
Haryana	- 5.90	0.99	6.15	- 1.01	- 3.73	2.41	- 8.31
Gujarat	- 2.64	-0.73	1.47	- 1.29	- 8.11	- 8.64	6.00
Karnataka	3.08	3.20	1.98	0.39	- 4.91	0.65	2.43
Delhi	3.13	2.48	1.13	3.12	-12.17	- 5.44	8.57
Madhya	5.62	1.72	3.60	2.86	4.05	12.22	- 6.61
Rajasthan	10.19	0.98	4.04	4.30	11.72	21.03	-10.84
Orissa	29.99	-3.55	- 0.10	17.41	23.36	37.11	-7.13
Bihar	31.00	-4.38	6.47	3.13	- 0.09	5.12	25.88
West Bengal	42.63	-7.78	- 0.75	3.86	4.40	- 0.27	42.90
Maharashtra	49.40	1.32	12.05	4.91	- 3.68	14.59	34.81
India	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Figures are in percentages. See notes to **Section 4.1**. Weights used are N_{is}/N_s.

TABLE 4.2b

HOW MUCH OF THE STATE WAGE DIFFERENTIAL DOES THE ESTIMATED EQUATION EXPLAIN ?

Industry composition is held constant

State	(1) Nominal wage differential	(2) Cost of Living	(3) Outside wage	(4) Productivity	(5) Days per worker	(6) Size of factory	(7) Explained variation (2+3+4+5+6)	(8) Fixed Effect
Andhra	-20.62	0.51	-12.97	-11.64	- 8.65	1.28	-31.46	10.83
Kerala	24.89	0.68	-10.94	-10.14	8.02	6.53	- 5.85	30.74
Punjab	-15.57	- 0.33	- 3.50	- 3.11	- 3.67	- 3.14	-13.74	- 1.83
Uttar	- 2.56	1.02	- 2.13	- 1.88	- 7.41	4.42	- 5.97	3.41
Tamil Nadu	- 4.50	0.99	- 1.47	- 1.28	1.89	- 0.59	- 0.47	- 4.03
Haryana	- 5.55	0.81	- 1.26	- 1.10	15.12	3.95	17.51	-23.07
Gujarat	-12.76	- 0.72	- 0.29	- 0.23	2.13	- 3.13	- 2.23	-10.52
Karnataka	0.13	2.47	0.69	0.65	3.51	0.52	7.84	- 7.71
Delhi	0.11	1.70	1.09	1.00	- 2.73	-12.81	-11.75	11.86
Madhya	- 8.51	1.03	1.47	1.34	1.87	3.76	9.45	-17.97
Rajasthan	2.68	0.78	2.37	2.15	- 0.93	5.41	9.78	- 7.11
Orissa	-19.34	- 1.99	3.63	3.27	-17.30	- 3.95	-16.35	- 3.00
Bihar	3.38	- 2.76	7.34	6.60	- 6.47	- 3.92	0.79	2.60
West Bengal	39.75	- 5.69	8.70	7.82	0.86	2.30	13.99	25.75
Maharashtra	42.00	0.95	10.93	9.81	20.73	1.05	43.47	- 1.47
INDIA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: All figures are in percentages. See **Section 4.1**.

and virtually all of the total variation in earnings. We have noted work intensity differences between *industries* in the preceding section. As in the case of productivity effects, what catches attention here is that there remain large differences in work intensity between the states *after* controlling for industrial composition (**Table 4.2b**). And again, there are some interesting reversals in rank between **Tables 4.2a** and **4.2b**. Notice Kerala and Orissa, for example. There is a popular view that Kerala's factory workers are 'stroppy' and similarly, a commonly held view is that Punjabi's are hard working people. Both views are negated by the evidence in col.5 of **Table 4.2b**. It is also worth marking out Maharashtra, which is industrially the most prosperous state. As the 'new' industries are centred around Maharashtra in the west, one might suspect that its industrial composition explains virtually all of its relative success. In fact, it has the largest positive wage differential even when composition effects are removed (**Table 4.2b**, col.1) and half of this is accounted for by its exceptionally high work intensity. Average *factory size* also makes a powerful contribution. Not surprisingly, this is somewhat attenuated when industry composition is held constant.

The state *fixed effects* explain the largest part of the variation in state wages. In more than half of the states, the fixed effects are powerful enough to counteract the effects flowing from the other explanatory variables. Notice, for instance, Punjab and West Bengal in **Table 4.2a** and Kerala and Madhya Pradesh in **Table 4.2b**. The coefficient of variation of the fixed effects is about half as large as that of earnings. When it is taken into account that states have different industry compositions, the correlation between the state fixed effects and state earnings is 0.81, which is significant at 1%. However, if composition is held constant, this correlation falls to 0.50, which is significant at 6%. Finally, note that the correlation of the fixed effects in **Table 4.2a** with the fixed effects in **Table 4.2b** is 0.24, which is insignificant (p=0.38).

What factors underlie the state fixed effects?

The fixed effects from **Tables 4.2a-b** are correlated with a wide range of state-specific variables. It is of some interest that the correlation of both sets of fixed effects with the following variables is *insignificant*: the infrastructural development of the state, the rural wage, the state minimum wage, the literacy rate, the proportion of young adults in the state, days lost in strikes per worker, and trade union density. Significant correlations are in **Table 4.4a**. It is also interesting that no correlate of the fixed effects in column 1 is a correlate of the fixed effects in column 2. For example, if industrial composition is held constant, being in a metropolis is of no consequence for wages.

Table 4.4a
EXPLAINING THE STATE FIXED EFFECTS ON WAGES
Pearson Correlation Coefficients

Variable	Fixed effect (variable composition)	Fixed effect (constant composition)
unemployment rate		0.80
left wing dummy		0.82
metropolis dummy	0.68	
public sector concentration	0.49	
low caste popu.(%)		-0.11
higher education(%)	0.52	
absenteeism rate		-0.54
construction wker(%)	-0.56	
p.c.real state NDP	0.49	
rural popu. density		0.69

Notes: Reported correlations are significant at 5%. Variables not significantly correlated with either fixed effect are not listed here.

In **Table 4.4b,** we investigate the regional wage determinants identified in **Chapter 2**. The fixed effects from **Table 4.2a** are regressed on state unemployment and a set of variables that may be interpreted as either wage pressure factors or relevant aspects of the labour force composition of the state. The results are broadly similar to those in **Chapter 2.** Regional unemployment, which we were not able to include directly in the wage equation, has a significant negative impact on wages through the state fixed effects. There is a weakly positive literacy effect and a robust age effect in the expected directions. Wages are permanently higher if the region has a left-wing government, a large metropolis, or a high ratio of public to privately owned company capital. It should be emphasized that these results obtain after controlling for industry-state-year variations in productivity, work intensity, factory size, the cost of living and, in the constant composition case, the alternative wage.

Table 4.4b
EXPLAINING THE STATE FIXED EFFECTS ON WAGES
Regression Analysis
Dependent Variable= ln(state fixed effect)

usual status unemployment rate (%)	*public/pvt. company capital*	*metropolis dummy*	*left-wing dummy*	*%(15-29) year olds*	*literacy rate (%)*	*intercept*
-7.1 (2.4)	0.046 (1.8)	0.15 (2.5)	0.28 (2.1)	-1.36 (2.4)	0.40 (1.7)	-2.44 (5.0)

Notes: N=14; R^2=0.75, Adjusted R^2= 0.54; F-statistic=3.6 (p-value=0.06); root MSE=0.08. These are OLS estimates. 2SLS estimates obtained by specifying instruments for the unemployment rate are not significantly different. All variables other than the unemployment rate are in logs. The unemployment rate is entered in percentages. The unemployment *elasticity* -0.41, given a mean of 5.9%. The fixed effects are from **Table 4.1a** where industrial composition is allowed to vary across states.

4.2.3. The Development of Wages over Time

The general conclusion from looking at a decomposition of the variation in industry and state earnings is that the variables identified as significant in our regression analysis explain, on average, no more than a third of the *cross-sectional* variation. However, **Table 4.3a** shows that the *time* variation in earnings is almost entirely explained by these variables. Col. 2 shows that growth in nominal wages closely tracks growth in the *cost of living* and that productivity growth accounts for about a fourth of the temporal variation in earnings in the 80s. These results imply that it is not difficult to explain the acceleration in factory earnings from the 1970s to the 80s (**Chapter 4, Tables 2 & 3**), since it is only in the 1980s that consumer prices leapt ahead of industry prices (**Chapter 4, Table 6**), and there was rapid productivity growth (**Chapter 5, Table 2.5**). While cost of living adjustments were probably effected by unions, one does not need to stipulate a rise in union power in order to explain rising wages. Yet, this is what has been proposed (eg. Sengupta 1988, World Bank 1989; see Section 6.2, **Chapter 4**). While the other variables are non-negligible, their contribution pales in comparison.

Of course, it is not surprising that the nominal wage is mostly explained by nominal variables. For this reason, the decomposition is repeated for the *real wage* (w_t-cpi_t) in **Table 4.3b**. *Productivity* (π_t-cpi_t) continues to explain about a fourth of the inter-year variation in real wages. While the contribution of the 'real variables', *days per worker* and average *factory size*, is of the same absolute size, their share of the variation explained is larger now.

TABLE 4.3
HOW MUCH OF THE TEMPORAL VARIATION IN WAGES DOES THE ESTIMATED EQUATION EXPLAIN?

	TABLE 4.3a: *NOMINAL* WAGES							TABLE 4.3b: *REAL* WAGES					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)
Year	*Nominal* wage diffl.	Cost of living	Nominal prody.	Days per worker	Size of factory	Explained variation 2+3+4+5	Fixed effect	*Real* wage diffl	Real prody.	Days per worker	Size of factory	Explained variation 2+3+4	Fixed effect
1979	-38.09	-22.68	- 9.92	- 1.83	0.23	-34.19	-3.90	- 8.88	-2.27	-2.19	0.27	-4.19	-4.69
1980	-31.59	-16.87	- 8.83	- 3.11	0.12	-28.68	-2.91	- 9.98	-3.26	-3.54	0.14	-6.66	-3.32
1981	-24.25	- 9.54	- 5.89	- 3.69	-0.87	-20.00	-4.25	-12.17	-2.70	-3.96	-0.94	-7.60	-4.57
1982	-13.29	- 5.42	- 3.99	- 3.03	1.53	-10.91	-2.38	- 6.18	-2.16	-3.15	1.60	-3.71	-2.48
1983	3.72	2.67	2.23	2.66	0.59	8.15	-4.43	0.10	1.26	2.61	0.58	4.45	-4.35
1984	17.07	7.89	4.06	3.39	0.74	16.08	0.99	6.08	1.21	3.23	0.70	5.14	0.94
1985	30.74	13.96	7.95	3.66	-0.67	24.90	5.84	10.87	2.77	3.36	-0.62	5.51	5.36
1986	43.47	22.12	11.83	3.97	-0.75	37.16	6.31	11.88	3.51	3.49	-0.66	6.34	5.54
1987	57.84	31.83	14.49	1.62	-1.43	46.50	11.33	12.33	2.69	1.35	-1.19	2.85	9.48

Notes: All figures are in percentages, prody=productivity. See **Section 4.1**.

On average, days per worker explains more than a third of the total variation. But size still has virtually no effect, which is not surprising as most of the variation in this variable is cross-sectional. While the *time dummies* (col.7) explain only 5%-15% of the variation in nominal earnings, they explain 30%-50% of the variation in real earnings. These unspecified year effects will include the effects of aggregate unemployment and wages. Therefore we may conclude that outside market factors account for about half of the time variation in real wages, the other half being on account of time-varying industry-state specific factors.

PART 5: SUMMARY AND CONCLUSIONS

Summary of the main argument

In this chapter, we have investigated wage determination in Indian factories. The analysis is motivated by the observation that factory wages exceed subsistence requirements by a wide margin, even as there is an excess supply for factory jobs. In **Chapter 2**, we found some evidence of queueing for factory jobs, which suggests that the wage premia accruing to factory workers cannot simply be explained away by systematic differences in personal and job characteristics between factory and other workers. The basic hypothesis, namely that the labour market is imperfectly competitive, gains considerable support from the evidence gathered here. We now summarize the main features of the argument.

Mazumdar (1988) isolates a clear size effect on firm wages which persists after controlling for worker attributes (Part 1). Mazumdar (1973) cites historical evidence to show that uncompetitively high wages in Indian manufacturing are not primarily on account of trade unions and government interventions. This is the first suggestion that Indian employers pay efficiency wages. It is reinforced by our description of the inter-industry wage structure in Part 2. The standard deviation of the industry distribution of log earnings is 0.46, which is very large by international standards, and the earnings structure is very stable over time. These facts are difficult to reconcile with competitive labour markets. In addition, India's industry wage structure is significantly correlated with that in the U.S., which in turn, is very similar to that in many other nations. This undermines the importance of institutional factors including unionism.

Having acquired a strong hunch that efficiency wages are paid, and acknowledging the prevalence of unions in India, in Part 3 we have set out a model of wage determination that encompasses both features. This is estimated for production workers in Indian factories, a single occupational group being chosen to limit skill differences between sectors. We find a significant role for industry-specific variables in determining the industry wage. In particular, the elasticity of wages with respect to productivity is 0.21. This is robust to inclusion of time dummies and industry-specific trends. There is also a significant size effect on wages of 0.13. The first is not consistent with perfectly competitive labour markets, and while the second is, research into this effect by other authors, together with Mazumdar's (1988) argument for India, suggests that it is more likely a reflection of rent-sharing or of the payment of efficiency wages. The joint insignificance of the time dummies indicates that aggregate variables have no strong independent effect on the wage, reinforcing our view of labour markets segmented along industry and state lines. While the signs of imperfect competition are robust, it is not clear what weight the 'inside' factors have against the 'outside', nor is it clear how much of the actual variation in wages is explained by the estimated equation. So, in Part 4, we investigate this using the wage equation estimated in Part 3. Productivity accounts for, on average, about a fourth of the total industry variation in earnings, though it explains virtually all of the wage differential in Petroleum, and almost none of the wage differential of Cement etc. The 'time decomposition' shows that productivity accounts for about 25% of earnings variation. More striking is the finding that unidentified fixed industry effects explain more than half of the variation in earnings between industries. The industry dispersion in these is 0.23, which is very substantial. While the fixed effects may incorporate unobserved quality differentials, we hypothesize that they also include union effects that are difficult to quantify and technology effects that are not captured by productivity and size.

Contributions and other findings

The transparent contribution of this work is that, as there is no similar investigation for India, it offers some new results. We find that factory wages are determined by productivity, factory size, work intensity, the regional cost of living and comparison wages in the region. The regional unemployment rate has a negative impact on wages (elasticity= -0.41), which is identified through its impact on the fixed effects in the wage equation. In **Chapter 2**, an unemployment effect of similar size was identified directly. Evidence of hysteresis is confined to 3 out of 18 industrial sectors. The identified variables explain 80-90% of the time variation in wages and, at best, half of the cross-sectional variation. The analyses of the industry wage structure in Parts 2 and 4 increment the accumulating international evidence that sectoral affiliation is significant in explaining workers' earnings (eg., Katz and Summers, 1989). A shortcoming of our analyses is that we do not control for job and worker characteristics. On the other hand, no other study appears to have identified industry effects on wages after controlling for observable *sectoral* variables, using their 'true' coefficients, which are identifiable from panel data. As far as I know, this is the first study to conduct a parallel analysis of regional wage differentials. Interesting results are as follows. There are substantial inter-state differences in productivity and work intensity even after controlling for industrial composition. Moreover, there are huge state fixed effects on wages, a strong statement on segmentation of the Indian labour market along state lines. Permanent state wage differentials obtained after controlling for observable factors are found to be related to long run unemployment rate differentials and other variables discussed in **Chapter 2**.

The model of wage determination in Part 3 incorporates some innovative features. We are able to distinguish visible and invisible effort. Of relevance to the analysis of employment in **Chapter 4**, we find that additional days are less expensive than additional workers. Size appears as an explicit variable in our model, and is significant even after controlling for productivity. The availability of industry data disaggregated by location enables us to specify the alternative or comparison wage as the average state wage. We investigate real wage resistance and find that it is significant. In an agrarian economy the wedge between the cost of living and the price of manufactures can be significant. The joint behaviour of product wages and the price wedge have inspired interest in India in the context of the wage-goods constraint (eg., Chakravarty, 1974) but, so far, the quantitative evidence has been lacking. The fact that workers succeed in obtaining cost of living adjustments may be regarded as evidence that unions in the factory sector do wield some power. Alternatively, if efficiency wage considerations predominate, then it appears that efficiency depends on the consumer wage[36]. Of course, efficiency wage payments and union bargaining over wages can operate in conjunction with each other. The wage equation is estimated on an industry-region panel for 1979-87. The advantage of a panel is that we are able to identify the correct coefficients on the time-varying variables, and to avoid compositional biases arising from structural change that alters the weight of a given industry-state unit in the aggregate. The specification can incorporate unrestricted dynamics and controls for unobserved fixed effects as well as for aggregate effects common across industry-state pairs. This is why the wage equation in this chapter is an improvement on that in **Chapter 2**. We use the GMM estimator proposed by Arellano and Bond (1991). This is an efficient instrumental variables estimator that gives consistent estimates even on a short panel.

The significance of sectoral wage differentials

Since Parts 2 and 4 concentrate on sectoral wage differentials, it is worth considering their significance in the context of policy, or more simply, in characterizing a less industrialized economy. A glaring feature of the Indian labour market, and indeed of any developing country labour market, is segmentation. The classic segmentation is the rural-urban dualism (which arose in the discussion in **Chapter 2**). A further well-established dualism is that between the formal and the informal sectors of the urban labour market. A less well-recognized fact, and one that is underlined here, is that there are multiple segments within the formal sector. Having concentrated in **Chapter 2** on segmentation along state lines, we concentrate now on segmentation along industry lines.

Non-competitive wage setting is of interest because it implies that the existence of substantial unemployment, or more generally, a large labour surplus[37], will not 'beat down' wages

[36] This is investigated in **Chapter 6**.

[37] Not all of the labour surplus in a LIE is unemployed because most workers cannot afford unemployment. There are various forms of underemployment, which have competitive properties similar to unemployment,

sufficiently to clear the labour market[38]. What are the important consequences of this? In developed countries, it implies a danger of untamed wage inflation arising from a wage-price spiral, given imperfect competition in product markets. The same process is possible in India, given the oligopolistic nature of registered sector industry. However, it is unlikely to be as central, given that (a) the share of labour costs, at 40%, is outweighed by the share of material costs in production, which is 60% (see Chatterji, 1989); and (b) the consumer price index is dominated by food prices, the prices of factory goods being relatively insignificant (Tulpule and Dutta, 1988). Instead, in a developing country like India, the more crucial fear is of growing unemployment. Although the unemployment rate has not grown alarmingly, rural proletarianization (Vaidyanathan, 1994), casualization of the urban work force (Minhas and Majumdar, 1987), and increasing self-employment of urban workers (Vaidayanthan, 1994) are indications of the growing paucity of good jobs in the economy. At the same time, the *numbers* unemployed in the urban sector have been rising, though this has not shown up in the urban unemployment *rate* (Table 1, **Chapter 2**) because accelerating urbanization has caused the urban labour force to swell *pari passu*. Small as it currently is, the manufacturing sector is expected to drive job-creation in the economy, and so to effect the structural transformation. This process however comes up against a rigidity that was not envisaged by development planners, namely that worker effort is an important determinant of productivity, and needs to be nurtured, *inter alia*, by the provision of wage incentives. If this is correct and Indian firms pay efficiency wages (**Chapter 6**), there is little that policy measures can achieve. The important question is of the extent to which the long run productivity gains translate into higher employment and how long the long run is[39].

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since the underemployed would typically like to move up to a 'good job'.

[38] It should be noted that this is not to say that the wage is *strictly* downwardly rigid, as that would require that it is insensitive to unemployment. In **Chapter 2**, we have established that it is not.

[39] In the long run, the existence of insider wage setting has no implications for the employment effects of technical change. The fact that insiders can capture productivity gains in the short run is irrelevant because competitive forces in the product market ensure that these gains are eventually spread through the population

CHAPTER 4
THE DECLINE IN MANUFACTURING EMPLOYMENT

1. THE CONTEXT

In the early 1980s, the factory sector emerged from more than a decade of stagnation with output growth at least as healthy as in the high-growth phase following the implementation of planned industrialization. Concomitant with this resurgence of growth was little or no increase in employment. Between 1982 and 1983, about 0.185 million jobs were lost, a decline of 2.4%. On average, the growth rate of employment between 1979 and 1987 was negative (-0.3% p.a). Although an actual decline in employment was confined to 5 of 18 two-digit sectors, deceleration was across-the-board. In contrast, though the preceding period (1965-1979) was one of low growth, employment kept pace with output (**Table 1**). In this chapter, an attempt is made to understand the reasons for the distinct slowdown in the growth of factory employment in the period 1979-1987. **Tables 2** and **3** present industry and aggregate growth rates of relevant variables for the 1980s. **Table 4** presents growth rates of chosen variables for the 1970s.

Table 1
Value added, Capital Stock and Employment in the Factory Sector
Aggregate growth rates by sub-period

Period	Value added	Employment	Capital stock
1959-1965	9.1	4.0	13.4
1965-1979	5.0	3.5	7.0
1980-1985	7.5	-0.7	7.6

Notes & Sources: Adapted from Table 3.1, Ahluwalia (1991). Our estimates of growth rates for the 1980s (**Table 2**) refer to 1979-87 rather than 1980-85.

1.1. Employment growth in a less industrialized country

In **Chapter 2**, we were primarily interested in the processes generating open unemployment in India. We approached this question by studying properties of the geographic distribution

Table 2
***The 1980s:* Trend Growth Rates by Industry**
VALUE ADDED, CAPITAL AND LABOUR

	value added	*capital*	*employees*	*days/employee*
Chemicals	6.62 (7.3)	6.74 (28.5)	1.49 (5.6)	1.45 (7.2)
Cotton textiles	0.33 (0.3)	5.70 (25.7)	-3.56 (8.7)	1.59 (4.3)
Electricity	1.26 (0.7)	6.75 (12.8)	2.64 (3.6)	-0.10 (0.6)
Electrical machinery	8.71 (6.2)	8.47 (16.3)	1.89 (4.5)	0.70 (4.9)
Basic metals	1.25 (1.3)	6.26 (22.5)	1.21 (2.2)	1.01 (4.3)
Food products	8.89 (3.6)	6.65 (23.4)	-4.10 (4.1)	6.47 (5.7)
Jute textiles	-4.14 (1.6)	3.50 (10.3)	-4.04 (3.1)	0.07 (0.2)
Leather products	7.48 (4.2)	11.5 (29.6)	3.23 (7.4)	0.65 (5.1)
Machinery	5.35 (5.4)	6.54 (11.3)	0.49 (1.0)	0.45 (2.2)
Metal products	3.50 (3.3)	6.86 (15.0)	-0.65 (1.0)	0.61 (3.3)
Cement,glass etc	9.81 (11)	12.0 (22.0)	2.92 (4.6)	-0.37 (0.4)
Other products	13.6 (7.6)	9.49 (11.5)	1.19 (2.5)	0.31 (0.9)
Petr & rubber	13.6 (5.1)	12.1 (30.4)	1.61 (2.9)	2.38 (4.6)
Paper & print	4.47 (4.6)	8.71 (12.1)	0.14 (0.2)	0.44 (2.8)
Tobacco & beverages	7.20 (3.1)	11.8 (6.2)	-0.65 (0.5)	2.44 (3.2)
Transport equipment	4.82 (4.7)	4.92 (6.4)	-0.14 (0.3)	0.87 (5.1)
Textile products	6.00 (3.0)	10.6 (5.1)	2.24 (2.8)	0.69 (2.9)
Wood products	2.08 (1.7)	5.56 (2.3)	-2.12 (7.0)	0.67 (2.9)
Wool & silk textiles	7.37 (7.9)	11.2 (23.9)	3.59 (5.8)	0.77 (2.5)
Manufacturing	6.30 (7.8)	7.0 (18.2)	-0.28 (0.88)	1.64 (6.7)

Notes: Value added is deflated by an industry price index (P_{it}). Data refer to 1979-87. Growth rates (%) are obtained as β where $\ln X = \alpha + \beta(\text{trend})$. Absolute t-ratio in parentheses. *Source:* Author's own calculations, based on ASI data (CSO), various issues.

of unemployment, emphasizing its stability to the relative neglect of trends. Here, we are interested in aggregate trends. Insofar as trends can be discerned from quinquennial data, **Table 1** in **Chapter 2** reveals no tendency for the urban unemployment rate to rise between 1977 and 1987. This is interesting because it appears to contradict the fact that there was little growth in manufacturing employment in this period. In fact, there is no necessary contradiction. Only about 30% of India's urban work force is employed in manufacturing. Moreover, a reduction in employment opportunities may be reflected in a swelling of the numbers in casual or self-employment, rather than in higher unemployment rates. Thus, (in Gujarat), Patel (1990) notes that most of them resorted to self-employment and to wage labour in the informal sector. Minhas and Majumdar (1987) note a rising trend in the percentage of casual workers in both rural and urban areas and Vaidyanathan (1994) documents an increase in the proportion of self-employed workers in the urban sector in the 1980s. It is important to recognize that in a poor country, manufacturing employment and urban unemployment are not two sides of the same coin.

A powerful doctrine of the development economics literature in the 1950s and 1960s was that industrial growth would not only launch economic development, but would also draw surplus labour off the land and into more productive employment (eg, Lewis, 1954). The experience of the developing world in the 1970s and 1980s has been disappointing in this respect. The share of agricultural in total employment has begun to shrink in most developing countries, including India (see Krishnamurthy (1984) for India and Chenery, Robinson and Syrquin (1986) for some other developing countries). However, industrial employment has grown rather slowly and its share has increased from 11% in 1951 to only 16% in the early 1990s (Papola, 1992). The failure of economic development to generate sufficient employment in a labour-abundant country is symptomatic of inefficient resource allocation and of the limited spread of the benefits of development.

Employment generation has been a primary concern of Indian development policy throughout the post-Independence period (1947- .). Planned development followed the Mahalanobis strategy of "heavy-industry first", geared at achieving a high rate of economic growth in the long term. In recognition that employment growth may not keep pace with the growth of the labour force in the medium term, discriminatory measures to encourage labour-intensive industries were introduced (Vaidyanathan, 1994)[1]. However, it was only in the early 1970s, when it was then clear that growth was not trickling down to the poor,

[1] Prime among these is the small scale industries policy. Since June 1991, when IMF conditionalities were set in force, protection of the small (non-factory) sector is being cut back (Acharya and Acharya, 1995). This means that factory sector employment will be in even greater focus in the 1990s than it has been so far.

Table 3
***The 1980s:* Trend Growth Rates by Industry**
PAY AND PRODUCTIVITY RATES

	real *earnings*	**real *wage***	**value added/ employee**	**value added/ day**	**capital productivity**	**capital intensity**
Chemical products	5.57 (11.0)	4.13 (7.4)	5.12 (6.3)	3.68 (4.6)	-0.12 (0.1)	5.24 (17)
Cotton textiles	6.13 (11.0)	4.56 (9.6)	3.89 (3.1)	2.30 (1.8)	-5.37 (4.4)	9.26 (28)
Electricity	0.09 (0.1)	0.18 (0.2)	-1.39 (0.8)	-1.29 (0.7)	-5.49 (2.9)	4.11 (8.3)
Electrical mach	6.44 (13.0)	5.74 (16)	6.81 (6.1)	6.12 (6.0)	0.23 (0.2)	6.58 (13)
Basic metals	0.42 (0.7)	-0.59 (1.1)	0.05 (0.0)	-0.96 (0.8)	-5.01 (5.9)	5.05 (14)
Food products	10.6 (4.5)	4.14 (2.9)	13.0 (4.2)	6.52 (3.1)	2.24 (0.9)	10.7 (10)
Jute textiles	5.37 (1.7)	5.30 (1.8)	-0.10 (0.0)	-0.17 (0.1)	7.63 (2.7)	7.54 (7)
Leather products	3.22 (3.6)	2.58 (3.1)	4.25 (2.5)	3.60 (2.2)	-4.02 (2.2)	8.27 (12)
Non-elec mach	4.59 (11)	4.14 (12)	4.86 (6.1)	4.41 (6.5)	-1.20 (1.3)	6.05 (11)
Metal products	4.55 (5.8)	3.94 (6.0)	4.16 (5.8)	3.55 (5.6)	-3.35 (3.6)	7.51 (13)
Cement,glass, etc	2.42 (2.7)	2.79 (2.1)	6.89 (11)	7.26 (5.8)	-2.23 (2.0)	9.12 (11)
Other products	9.15 (18)	8.84 (22)	12.4 (6.4)	12.1 (6.0)	4.11 (1.9)	8.30 (11)
Petroleum &rub	4.98 (6.5)	2.60 (3.1)	11.9 (4.8)	9.57 (3.7)	1.41 (0.5)	10.5 (14)
Paper and printing	4.10 (8.1)	3.66 (9.0)	4.33 (3.7)	3.89 (3.8)	-4.24 (4.7)	8.57 (12)
Tobacco & bev	3.58 (1.7)	1.14 (0.5)	7.85 (3.1)	5.41 (2.0)	-4.61 (1.6)	12.5 (5)
Transport eqpt	5.25 (11.0)	4.38 (9.2)	4.95 (7.4)	4.08 (6.0)	-0.10 (0.1)	5.05 (5)
Textile products	1.04 (0.7)	0.34 (0.3)	3.76 (1.8)	3.06 (1.5)	-4.55 (1.8)	8.31 (6)
Wood products	4.77 (5.8)	4.10 (5.3)	4.20 (3.9)	3.53 (3.2)	-3.47 (1.9)	7.67 (3)
Wool &silk tex	3.37 (4.6)	2.61 (3.5)	3.78 (3.3)	3.01 (2.6)	-3.80 (3.3)	7.58 (21)
Manufacturing	5.63 (7.0)	4.24 (6.7)	6.60 (5.5)	4.96 (5.0)	-0.69 (1.9)	7.25 (12.7)

Notes: See notes to **Table 2**. *Earnings*=annual income, *wage*=income per 8-hour day of work. Incomes and value added are deflated by the industry output price (P_{it}). *Source:* Author's calculations, based on ASI, various issues.

that policy efforts at employment generation were intensified. Mrs. Gandhi's *Garibi Hatao* (Remove Poverty) programme, a landmark venture, was initiated at this time. Since then a variety of employment programmes have appeared, culminating in the *Jawahar Rozgar Yojna* (the Jawahar Work Plan). While these schemes appear to have made a dent on the problem (Vaidyanathan, 1994), their impact is local and their implementation fraught with administrative problems like targeting. Certainly, despite these efforts, employment growth rates in agriculture, manufacturing, transport and services have declined continuously through the three quinquennia in 1972-87 (Planning Commission, 1990). In 1987/88, there

Table 4
The 1970s: **Trend Growth Rates by Industry**
EMPLOYMENT, EARNINGS AND PRODUCTIVITY

Industry	employees	real earnings	value added/ employee	Industry	employees	real earnings	value added/ employee
Chemical prod	6.65	0.02*	0.20*	Metal products	2.13	1.84*	1.25
Cotton textiles	2.39	2.26	1.89*	Cement,etc	3.02	1.73	0.09*
Electricity	5.60	4.68	2.71	Other	1.33*	3.15	0.59*
Elec. mach	3.69	2.13	3.20	Petr &rubber	6.06	-1.74*	-1.13*
Basic metals	3.52	1.39	1.88*	Paper &print	0.92*	1.61	1.70
Food products	7.46	-2.25*	-2.53*	Tobacco & bev	12.78	-2.12*	-8.93
Jute textiles	1.74	1.64*	2.32*	Transport eqpt	0.78*	2.00	1.84*
Leather prod	7.25	3.19	6.89	Textile prod	6.87	1.40*	3.84*
Machinery prod	3.57	2.93	3.46	Wood products	0.95*	1.12*	-0.99*
Manufacturing	4.78	2.21	1.15*	Wool& silk tex	7.27	1.01*	0.45*

Notes: See notes to Tables 2 & 3. The data are for 1970-79. An asterisk denotes growth rates that are insignificantly different from zero. These growth rates are not strictly comparable with those in Tables 2 and 3 although they make the point of the difference between the 1970s and the 1980s. *Source*: Jose (1992).

were 12 million people in 'open' (*usual status*) unemployment and the volume of *daily status* unemployment was greater (definitions in **Data Appendix**). Although the labour force participation rate has been fairly constant (Visaria and Minhas, 1991), the rapid decline in the death rate accompanied by a continuingly high birth rate implies both a relatively high dependency ratio and an expansion of the labour force in the future. This fact threatens a rising volume of unemployed unless employment in the economy is stimulated.

2. EXISTING WORK ON MANUFACTURING EMPLOYMENT

2.1. Analyses of the 1980s Slowdown in Employment

In this section, we describe existing attempts to address the question of why there was no employment growth in Indian manufacturing during the 1980s despite record output growth. The World Bank (1989) attributes this to an acceleration in wage growth in the 1980s. The latter is, in turn, attributed to union power and to legislation designed to protect employment and wage levels in the factory sector. The claim that wage increases are a central part of the explanation is substantiated by an estimate of the wage elasticity of labour demand and the claims regarding wage growth are not investigated. We contend both claims, and show that the World Bank's wage elasticity is spurious. We provide what we regard as more robust estimates of an employment equation for the 1980s and attempt to develop an alternative explanation of the recent employment experience.

Sengupta (1988) conducts an analysis very similar to that of the Bank and reaches the same conclusions. Although there is frequent allusion to the facts, there are no other econometric analyses. However, the Bank's study has drawn two important responses. In a passing reference to employment in her study of productivity, Ahluwalia (1991, pp.80-85) has corroborated the World Bank view. This stands out because of the wide circulation of Ahluwalia's book and the fact that it has emerged from an academic enclave that is in friendly proximity with the policy-making organs in India. The other is a significant contribution by Nagaraj (1994), the express purpose of which is to take issue with the stance of Ahluwalia and the World Bank. Using descriptive statistics for aggregate manufacturing, he shows that the 1980s were marked by the following trends, each of which makes the Bank's claims look weak: (a) Union power declined. (b) The real interest rate and the share of interest in production costs registered a steep increase. (c) 'Mandays worked' per worker increased. We had independently noted these facts and this study complements Nagaraj's by underwriting it with hard evidence. In view of the influence wielded by the World Bank and the paucity of analyses of the subject, we consider, *inter alia*, our quantification of the impact of true wage costs on employment to be worthwhile.

2.2. Other Estimates of the Employment Function in Indian Manufacturing

To our knowledge, there is no study of manufacturing employment in India that provides reliable estimates of the parameters of an employment equation. The existing studies are few (Diwan and Gujarati 1968, Krishna 1974, Goldar 1987) and refer to the period before 1980. These incorporate methodological flaws and so are poor models for future work. They all estimate the function N=N(W/P, Y), the theoretical underpinnings of which remain implicit (These are set out in **Appendix 4.1**). A lot of the confusion in thinking about variables like earnings, capital intensity and employment arises because they are all endogenous. Yet none of the existing studies allows for this at the time of estimation.

Table 5: Output & Employment
Sub-period growth rates

Period	*Output*	*Employment*
1951-65	7.4	3.0
1965-70	3.4	1.1
1970-75	3.6	3.0
1975-80	4.9	4.0

Source: Goldar (1987), Table 1. These are simple averages of annual growth rates. Here the 1960s and 70s are demarcated, which is not the case in (our) **Table 1**.

Goldar (1987) is the most accurate of these studies, though, like the World Bank, he mistakenly defines the wage rate as earnings, thereby ignoring work intensity. Nevertheless, we consider his results in some detail as his motivation is similar to ours. He is interested in explaining the fact that *employment growth did not slacken in the 1970s, even though output growth did* (**Table 5**[2]). We shall argue later (**Section 6.4**) that this fact is organically related to little employment growth in the 1980s despite rapid output growth. Goldar estimates the following equation on a panel of 20 industries, for 1960-1977:

$$\underset{(0.27)}{n = 2.75} + \underset{(0.03)}{0.68\, n_{-1}} - \underset{(0.04)}{0.35\, (e-p)} + \underset{(0.03)}{0.25\, y} + \theta_t + \theta_i$$

where the lowercase denotes logs, n=employment, e=earnings (=wage bill/n), p=product price index, y=output, θ_t=time dummies and θ_i= industry dummies. The implied long run earnings elasticity is -1.1. This falls in the neighbourhood of estimates obtained by the earlier studies cited above. Goldar argues that undampened employment growth in the 1970s was a consequence of deceleration in labour costs in that period. Indeed, earnings relative to a price index for manufactured goods grew at only 1% p.a. in the 1970s, a significant

[2] Goldar's employment data, like ours, is factory sector data from the ASI, except for 1951-56, for which he uses the Sample Survey of Manufacturing Industries. His output data refer to the index of industrial production in the National Accounts, which is known to behave differently from the ASI's output series (see Ahluwalia (1985), who argues that the ASI data are more reliable). So **Tables 1** and **5** are not comparable but each source provides internally consistent numbers.

drop from a growth rate of 4.2% p.a. in the 1960s. The drop is explained almost entirely by the fact that the price of manufactures accelerated, while growth in nominal earnings followed growth in the consumer price index, the rate of which did not change from the 1960s to the 1970s (see **Table 6**).

Table 6
Index Numbers Of
NOMINAL EARNINGS, OUTPUT PRICES AND CONSUMER PRICES

Year	Earnings	WPI	CPI	Year	Earnings	WPI	CPI
1960	100	100	100	1970	232	155	184
1961	106	105	104	1971	239	168	190
1962	116	106	107	1972	n.a.	178	202
1963	123	108	110	1973	287	200	236
1964	132	111	125	1974	341	244	304
1965	147	119	137	1975	367	259	321
1966	162	129	151	1976	368	257	296
1967	168	135	172	1977	403	268	321
1968	197	137	177	1978	435	266	329
1969	211	144	175	1979	478	305	358
			Annual growth rates (% p.a.)				
1960s	8.4	7.4	4.2	*1970s*	8.2	7.5	7.2
		1960-79	8.5	7.3	6.3		

Notes: Earnings are nominal emoluments of employees, WPI=wholesale price index for manufactured products and CPI=consumer price index for industrial workers. *Sources:* The index numbers are from Goldar (1987), Table 5. The growth rates are computed by the author as estimates from semilog regressions on trend.

2.3. The Status of the Labour Demand Curve

According to Neftci (1978), "The observed correlation between real wages and employment has puzzled macroeconomists ever since Keynes (1936). Several economists, including Kuh (1966), Bodkin (1969) and Modigliani (1977), have noted that the contemporaneous correlation between real wages and employment is usually not statistically significant, and even when it is, is often positive". Following the methodology of Sims (1974), Neftci shows that although signs of a labour demand curve are not forthcoming from estimation of a static model, a distributed lag model yields a negative employment-wage relationship for the U.S. economy. Neftci's explorations rely upon the existence of dynamics and have no theoretical underpinnings. These have been provided in later work (eg, Newell and Symons, 1988).

Neftci provides an interesting representation of a debate that was discussed from a somewhat different perspective in **Chapter 2** of this thesis. It is quite remarkable that so much confusion can have been generated and that elements of it still persist. Of course the correlation of the product wage and employment, contemporaneous or not, can go either way or be nullified altogether by balancing shifts in two relations[3]. The confusion arises from mixing the evidence on all of three distinct structural relationships. These are the migration equilibrium condition, the wage-setting function and the labour demand relation. The first is only relevant when the data refer to more than one region and is estimated in **Chapter 2**. A "cross-sectional form" of the wage function is also estimated there, and a "time-series form" is estimated in **Chapter 3**. Both embody *supply-side* mechanisms. In this chapter we turn to the *demand side*. The theoretical model of employment that is set out below shows that a negative effect of the wage on employment is inevitable in an appropriately specified labour demand schedule (**Section 3.2**).

3. THE THEORETICAL FORMULATION

The model of employment determination that we adopt as our *baseline model* is:

$$N=\psi(K, E/PD, \sigma^e, A), \tag{1}$$

where ψ incorporates the lags of the arguments, N=workers, K=capital stock, E=nominal annual earnings per worker, P=price index of industry output, D=days worked per worker, E/PD=daily product wage, σ^e=index of expected (cyclical) demand, A=index of technical progress. We shall later define $W=(E/PD)$.

3.1. A Steady State Employment Model

A steady state model consistent with (1) is derived from the production function and price-

[3] Indeed we find virtually no simple relation between these variables in the Indian data.

setting behaviour. Consider an economy with identical firms whose technology can be represented by the general production function:

$$Y = D\, f(A, N, K) \tag{2}$$

where f is unspecified, Y=real value added output[4] and the other variables were defined in (1). Firm-subscripts are omitted for neatness. Profit maximization with respect to employment gives the marginal productivity condition:

$$D\, f_2\,(A, N, K) = E/P \tag{3}$$

where $f_2=\partial f/\partial N$ is the marginal product of a standardized worker-day, and the left hand side expression is $\partial Y/\partial N$, the marginal product of workers. Rearranging (3),

$$N = h\,(K, A, W) \tag{4}$$

where we have defined the daily product wage rate W=(E/PD).

Imperfect competition in the product market

So far, P has been regarded as exogenous. In view of a significant degree of oligopolistic behaviour in India's registered manufacturing sector, we now modify the labour demand equation in (4). Under imperfect competition, price is endogenous to the employment decision. Once the price is set, a unique output level is determined on the product demand curve and, given the production function, this implies a certain level of employment. Thus a discussion of the employment decision in this environment requires the specification of price behaviour. Chakrabarti (1977) and Chatterji (1989) document evidence of markup pricing in Indian manufacturing. This is corroborated by our findings in **Chapter 5**, where we estimate the average markup in the 1980s to have been a substantial 48%. There is more

[4] Value added is deflated by the industry output price index, denoted as P in (1). We should really use a value-added price index, or else we should include an index of materials prices. Unfortunately, an industry-specific materials price index does not exist. Although there are aggregate time series on the prices of fuel, electricity, steel, cement, etc (Chandhok *et al*, 1990), input-output matrices are available only for *ad hoc* years. So, we rely on industry-specific trends to control for any industry-level heterogeneity in the growth of material prices.

widespread support for the markup pricing model (see Hall and Hitch 1952 and Coutts, Godley and Nordhaus, 1978)[5]. Maximizing profits with respect to N and allowing P to depend on Y yields the marginal revenue product condition:

$$P\ (1+1/\eta) = E/f_N \tag{5}$$

where $\eta=(\partial Y/\partial P)(P/Y)$, the product demand elasticity. Since the RHS of (5) is the marginal cost of labour, $(1+1/\eta)^{-1}$ is implicitly defined as the *mark-up* of price on marginal cost, which we shall refer to as ν. From (3), $f_N = D\ f_2\ (A, N, K)$. Using this in (5), we have:

$$N = g\ (K, A, \nu(\sigma^e)W\ ) \tag{6}$$

where $W=E/PD$ and the markup, ν, is allowed to depend on exogenous changes in expected demand, σ^e (see Stiglitz 1984 and Bils 1987). Equation (6) is not a *labour demand equation* because P and N are simultaneously determined. It is merely a rearrangement of the first-order condition for profit-maximization that describes the relationship between employment and the product wage[6]. Therefore, we refer to it as an *employment function*. The following features of (6) are of interest. First, suppose g is log-linear in its last argument, $\nu(\sigma^e)W$, as is true, for instance, when it is derived from a Cobb-Douglas production function. Then the wage elasticity of employment is independent of market structure, embodied in $\nu(\sigma^e)$. Second, significance of a demand term proxying σ^e is suggestive of imperfectly competitive product markets. Third, under perfectly competitive conditions, the elasticity of product demand, η, is infinite and so the mark-up, ν, is unity. Setting $\nu=1$ in (6) gives (4), which demonstrates that perfect competition is encompassed as a special case. Fourth, W is endogenous when firms are price-setters.

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[5] The administered price hypothesis was first proposed by Means (1935). He observed that the demand shock of the Great Depression in the early 1930s caused the prices of agricultural commodities to fall substantially (63%) while those of agricultural implements only decreased moderately (6%). This observation directed the attention of economists to the relation between market structure and the speed at which prices adjust to exogenous changes.

[6] A reduced form labour demand schedule can be obtained in the imperfect competition case by solving the first-order conditions simultaneously. The demand function, $Y=(P/P^a)^{-\eta}$ can be written as $P=P^aY^{-1/\eta}$, where P=firm (industry) price and P^a=industry (aggregate) price. Using this and Y=Df(A,N,K), we can substitute out P so as to write employment as a function of exogenous variables only: $N = N(E/DP^a, K, \nu(\sigma))$.

Imperfect competition in the labour and financial markets

The evidence in **Chapter 3** suggests that the labour market faced by India's factory sector cannot be characterised as perfectly competitive. We incorporate this into our current investigation by including the outside wage (W^a) in the model in a somewhat *ad hoc* fashion[7]. Nickell and Wadhwani (1990a) show how the financial position of a firm may impact upon its employment decision. Capital markets are known to be highly imperfect in poor countries, though this is complicated in India by government interventions that have (a) subsidized certain sectors and not others and (b) have adopted and maintained 'sick' (indebted) firms rather than let them exit. In view of this, it would be particularly interesting to investigate capital-labour market interactions of this sort in Indian industry. Recognizing that this is a question that is better tackled with firm-level data, we include an industry-level measure of liability (*L/K*).

Aggregation over firms gives the industry-level employment function. As little structure has been imposed on (6), the industry equation looks no different than the firm equation. In the next section, we look at the signs of some of the partial derivatives of the employment function, as predicted by theory.

3.2. Some Comparative Statics

The wage (W)

The long run effect of 'inside' wages on employment is negative, irrespective of the shape of the revenue function. Consider an exogenous rise in the wage rate from W_1 to W_2. Let the corresponding profit-maximizing levels of employment be N_1 and N_2. If R(N) is the revenue function then the following must be true:

$$R(N_1)-W_1N_1 > R(N_2)-W_1N_2$$

$$R(N_2)-W_2N_2 > R(N_1)-W_2N_1$$

[7] See Nickell and Wadhwani (1991) for a theoretical model of employment that incorporates labour market imperfections.

which implies that $0 \geq (N_1-N_2)(W_1-W_2)$. Since $(W_1-W_2)<0$ by construction, it must be that $(N_1-N_2)\geq 0$. In other words, a *ceteris paribus* increase in the wage rate cannot encourage employment (Bliss, 1988). Nickell and Wadhwani (1991) show that this remains true in a union bargaining model as long as the objective functions of the two parties have the standard properties, and the power of the union in the employment bargain does not exceed its power in the wage bargain[8].

The capital stock (K)

The positive impact of capital accumulation on employment is increasing in the product demand elasticity and decreasing in the elasticity of substitution between the factors. This is because, *ceteris paribus,* a rise in the capital stock will lower prices and hence increase demand but at the same time, it will cause some substitution away from labour. It can be shown that constant returns to scale (CRS) in production imply that the long run capital coefficient is unity (**Appendix 4.2**)[9].

The demand index (σ^e)

If the mark-up is counter-cyclical then prices will not rise as much as marginal costs in an upswing, which will reinforce demand and so cause employment to rise. Conversely, if the mark-up is procyclical then, given costs, prices are raised when demand is high. Since imperfectly competitive firms face downward-sloping product demand curves, a price rise implies a fall in output and employment. Thus the elasticity is expected to be negative if the mark-up is procyclical and positive if it is counter-cyclical. Although there is a considerable literature on the response of the mark-up and the marginal cost to the cycle, the direction of response is, *a priori*, not obvious (see Layard, Nickell and Jackman (1991),

[8] The standard properties are: (a) the wage-employment substitution elasticity in the union utility function is equal to one. This is true for most utility functions, e.g. utilitarian and Stone-Geary; (b) the share of labour in value added divided by the effort-employment substitution elasticity in revenue is less than one. The authors show this to be true irrespective of whether effort and employment are separable in the revenue function.

[9] However, if the 'inside' price which appears as the deflator of the 'inside' wage is substituted out by an 'outside' price (ie a price at a higher level of aggregation) then it is no longer the case that CRS implies a unit coefficient. Refer *footnote 6.*

pp. 339-341). It is even less obvious in India where features of an agrarian labour-surplus economy interact in complex ways with protection in the registered sector. Of particular interest, supply and demand linkages of the industrial and agricultural sectors may imply counter-cyclical labour costs (see for example, Chatterji (1989), pp. 52-55). The signs on these relations are thus best left to be empirically determined.

Efficiency (A)

If technical progress is *labour-augmenting*, it has two competing effects on employment. One is that it raises labour demand because the wage in efficiency units is lower. The other is that it reduces labour demand because less labour is required per unit of capital if labour is more efficient. It can be shown that, under CRS, the total effect is the negative of the wage coefficient ($-N_w$) minus the capital coefficient (N_k) in the employment equation (Layard and Nickell (1986), p.147). On the other hand, when technical progress is *neutral,* the impact on employment is positive.

3.3. Dynamics in the Employment Function

In practice, actual employment tends to deviate from its steady state level on account of costs entailed in adjusting the work force (Oi, 1962 and Holt *et al*, 1960). If costs of hiring, firing and training enter the profit maximand via some adjustment cost function[10], then employment will depend on its first lag. Or, if in response to a shock, the optimal behaviour of some firms is to adjust instantaneously and of others to maintain employment at the level of the preceding period, then industry-level data yield a partial adjustment model (Bresson *et al,* 1993). Longer lags that typically arise with quarterly or annual data may reflect serially correlated technology shocks or aggregation across different types of labour

[10] The adjustment function is usually taken to be quadratic. Concomitant with the availability of panel data in the 1980s, there have been theoretical advances in the formulation of the dynamic labour demand function. These have included non-linearities, complex adjustment cost specifications and allowances for heterogeneity of various sorts. Dormont and Sevestre (1986) and Bresson *et al* (1993) review these developments. Given the nature of our data, a relatively simple but general model serves our purposes and so no further consideration is made of these theoretical embellishments.

distinguished by different adjustment costs (Sargent 1978, Nickell 1986). In the absence of sufficiently disaggregated data, heterogeneity in the work force can be allowed for by specifying a more complex dynamic structure. Suppose that the basic employment model is AR(1) and the explanatory variables appear with k lags. Then if there are m groups of workers, each associated with different adjustment costs, total employment follows an AR(m) process and there are m+k-1 lags on the explanatory variables. Although adjustment costs are important, dynamics may arise for other reasons. They may represent the process of expectations formation or the costs of using labour more or less intensively. For example, overtime premia are incurred for increased time per worker while under-utilization of labour is costly where workers are paid for a standard week (eg., Mendis and Muellbauer, 1984). In the case of union models, a further potential source of dynamics is the fact that there are inter-dependent sequences of bargains. The precise form of lag structure implied by all of these elements is not straightforward. Therefore, the form that is initially taken to the data should allow a sufficiently rich employment lag structure.

Specifying dynamics in terms of autoregressive terms alone is equivalent to imposing a common time path for the impact of each explanatory variable on employment. This restriction may be valid if the cost of moving to the new target level is the only source of slow adjustment in the system and expectations are either static or formed identically for all variables in the model (Clark and Freeman, 1980). Wage contracts in India are written for between one and three years. This is a sufficient reason for the first condition to be violated. Further, there is no reason to believe that firms' expectations of their own future output are made in identical fashion to their guesses regarding, for example, the future real wage. This is because the latter depends to a large extent on the cost of living, which is driven by the performance of the agricultural sector, about which firms are likely to have less information. Therefore, we specify a general autoregressive distributed lag model. Insignificant lagged variables are then dropped to obtain a more parsimonious specification that remains consistent with the data. Implicit in our use of the Hendry approach (see Gilbert, 1986) is that we do not propose to be able to distinguish *a priori* between the various factors that underlie the dynamic structure of employment. This is because we are more interested in a good characterization of the processes the data describes than in upholding or refuting a particular model of adjustment.

4. AN EMPIRICAL SPECIFICATION

4.1. Data and Estimation Method

The data is a panel with a large cross-section and a short time dimension (see **Data Appendix**). It provides information for 1979-1987 on 18 industries disaggregated by location across 15 states of India. Three cross-sections are lost by first-differencing and taking two lags. Observations on 260 of the 267 industry-state pairs cover the continuous period 1982-87. For the remainder, the time series is shorter because of missing values. A survey of labour demand estimates across several countries (Hamermesh, 1993) indicates that availability of the regional disaggregation is a unique feature of the data set employed here. A major advantage of panel data is that it allows exploration of employment dynamics while reducing aggregation biases associated with time series data. Given that the 1980s was a period of phased macroeconomic and industrial policy changes which induced significant structural changes in manufacturing, the latter is particularly important. We use a GMM estimator (Arellano and Bond, 1991) which gives consistent estimates of models with endogenous regressors and heteroskedastic errors, even when the panel is short (see Section 3.2.2., **Chapter 3**). First-differencing purges the error of industry-state fixed effects and IV corrects for simultaneity and for measurement error biases that may arise from random corruptions in the data, as well as from the treatment of expectations, for example in σ^e (see following section).

4.2. The Variables

A general log-linear dynamic employment function estimated on panel data takes the form:

$$n_{ist}= \Sigma_j \lambda_j n_{ist-j} + \Sigma_j \beta_j x_{ist-j} + \theta_{is} + \theta_t + \varepsilon_{ist} \tag{7}$$

which says that the log of employment (N) in industry i, state s and year t is a function of its past values (going back to period t-j) and of a distributed lag vector of explanatory variables, X. In addition the model includes year dummies (θ_t), and fixed effects (θ_{is})[11]. We now proceed to flesh out this general form in accordance with the preceding discussion of the theory. From **Section 3**, we have

$$X = (K_{ist}, \sigma^e_{it}, W_{ist}, A_{ist}, W^a_{st}, L/K_{ist}) \quad (7a)$$

The **Data Appendix** defines these variables and their sources. Issues that arise in constructing the empirical specification are discussed here. The *dependent variable* is the number of *workers* (N_{ist}). As this includes casual and permanent workers who face different adjustment costs, we may expect to see two lags of the dependent variable in the equation. Though our primary interest is in the employment of people, we also investigate determination of the total labour input in *days* (M_{ist}). Exogenous *demand effects,* σ^e, are proxied by the realized change in real industry output (ΔY_{it}) (Alternatives in **Data Appendix**). Expectational errors fall into the equation error, and ΔY_{it} is instrumented. The *alternative wage* (W^a) is proxied by the state-average of factory wages (W_{st}). The average ratio of loans to capital stock is defined as a *liability index* (L/K_{ist}). The fixed effects (θ_{is}) capture heterogeneous *efficiency levels (A)*, and time dummies (θ_t) and industry-specific trends ($\theta_i t$)[12] pick up *efficiency growth or TFPG* (ΔA)[13]. Industry-year dummies (θ_{it}) are more general but, as they use up many degrees of freedom, they are confined to a variant of the model. Another variant includes a direct measure of TFPG, Δtfp_{ist} (see **Data Appendix**), which economizes on degrees of freedom and is industry-state-year specific.

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[11] Different industry-state units are assumed to have common slopes in (7). To investigate this, we would have to estimate a time series equation for each unit. With our 9 years, this is impossible, especially with dynamics in. Instead, we have estimated-an error correction form of the employment equation that enables direct tests on groups of heterogeneous parameters. The GMM estimates of the heterogeneous-slopes equation have large standard errors and so are disregarded. As a compromise, we have estimated employment equations first for each of the 18 industries and then for each of the 15 states. The null hypothesis of common long run slope coefficients cannot be rejected at the 10% level of significance but F-tests indicate the presence of heterogeneity in the equation dynamics. Inclusion of sector-specific trends is expected to control for this heterogeneity to some extent.

[12] This is consistent with the fact that the rate of output growth, a highly trended variable, is often regarded as a determinant of total factor productivity growth.

[13] The time dummies *comprehensively* account for macroeconomic influences that have a common effect on employment in different industries and states. This may include changes in labour legislation that apply uniformly, in addition to aggregate movements in TFP.

The error (ε_{ist}) is a stochastic term with mean zero that picks up employment surprises[14]. Thus, *in levels*, the empirical model is

$$n_{ist} = \theta_{is} + \theta_t + \theta_i t + \theta_s t + \Sigma_j \lambda_j n_{ist-j} + \Sigma_j \beta^1{}_j k_{ist-j} + \Sigma_j \beta^2{}_j w_{ist-j} + \Sigma_j \beta^3{}_j \Delta y_{it-j} + \Sigma_m \Sigma_j \gamma^m{}_j x^m{}_{(i)st-j} + \varepsilon_{ist} \quad (8)$$

All variables are in natural logarithms, Σ_j takes j from 1 to 3 and x^m=a vector of other variables that are not directly specified because they are of a more experimental nature. These include the alternative measures of TFP and σ^e discussed above, the alternative wage and the liability index. Variants that are estimated are: (i) An equation in which total *worker-days* replaces workers as the dependent variable; and (ii) An *output-constrained* model, given by (A.3) in **Appendix 4.1**.

5. RESULTS: EMPLOYMENT EQUATION ESTIMATES

The *capital model* discussed in **Section 5.1** corresponds to (8). The *baseline model* is its simplest version: N = N(W, K, A). Including additional variables gives the *extended model.* In **Table 7**, the dependent variable is employment and in **Table 8** it is days worked. The *output-constrained model* (**Section 5.2**) refers to (A.3) in **Appendix 4.1**, estimates of which are in **Table 9**.

5.1. Employment Conditioned On Capital Stock

<u>The baseline capital model</u>

Column (1) in **Table 7** reports the basic GMM estimates and, unless otherwise specified, our discussion refers to these. OLS-levels estimates of a model that includes industry *and* state fixed effects are in col.5 and WG estimates, which control for *industry-state* fixed effects are in col.4. Consider, the sum of the coefficients on the two autoregressive terms, obtained with the alternative estimators. As expected (see Section 3.2.2, **Chapter 3**), OLS-

[14] These surprise terms can be significantly large. For instance, the momentous textile strike of 1982-1983 will have resulted in large negative residuals (ε_{ist}) for employment in Textiles in Maharashtra in those years.

levels seriously over-estimates this number and WG under-estimates it. These results confirm the presence of sizeable industry-state fixed effects, and motivate the use of GMM. The GMM residuals display negative first-order serial correlation, as expected in a first-differenced model, and do not exhibit second-order serial correlation. So instruments typically include the second and more remote lags of the included variables, as well as external instruments when these improve the precision of the estimates. If the second lag of the dependent variable is omitted from the model, the dynamics are reflected in the residuals, which then exhibit serial correlation of second-order. Thus, the success of IV can depend upon correct specification of dynamics. The Sargan test of over-identifying restrictions demonstrates acceptance of our instruments at the 95% confidence level. It should be observed, though, that it has a tendency to be too kind (Arellano and Bond, 1991). The *number* of instruments chosen is a somewhat subjective matter. We present the results of estimating a first-differenced model using OLS (ie, OLS-FD), as a check against overfitting. Were we using too many *or* too few instruments, be they valid, our estimates would approach those of the OLS-FD model.

Employment dynamics

Two lags of employment are significant and the long run solution is well determined[15]. As the time dimension is short, the data probably cannot support too general a dynamic structure and further lags are insignificant (the point estimate of n_{t-3} is 0.002[16]). Both autoregressive terms being positive indicates a stable monotonic path to equilibrium. The implied speed of employment adjustment is **0.48**[17] **(see Appendix 4.3).** The median lag is

[15] In the absence of n_{-2}, sector-specific trends are significant and appear to proxy the second-order dynamics quite well.

[16] Goldar (1987) and the World Bank (1989) estimate employment equations which include only the first lag of the dependent variable, and most other studies of employment in India have specified static equations. In the absence of heterogeneous trends, omission of the second lag is not compensated by a rise in the coefficient on the first lag (col. 3, **Table 7**). Therefore ignoring second-order dynamics can cause a downward bias in the long run parameters, other things being equal.

[17] The estimated equation has the form:

$$(1 - \lambda_1 L - \lambda_2 L^2)n = x\beta + \varepsilon$$

Table 7
Employment Equations
THE 'CAPITAL MODEL'
Dependent variable= ln(workers)

	(1)	(2)	(3)	(4)	(5)	(6)
Method/Var	**GMM: baseline**	**GMM: impose CRS**	**GMM:drop n_{-2}**	**WG**	**OLS-levels**	**GMM: extended**
$(\text{dep.var})_{-1}$	0.18 (2.0)	0.20 (3.4)	0.18 (1.7)	0.195 (3.5)	0.51 (0.044)	0.24 (3.6)
$(\text{dep.var})_{-2}$	0.18 (4.0)	0.195 (5.0)		0.13 (3.1)	0.32 (0.047)	0.18 (2.9)
capital stock	0.44 (5.7)		0.49 (6.4)	0.31 (5.6)	0.16 (0.029)	0.37 (4.7)
correct wage_{-1}	-0.15 (2.5)	-0.16 (2.4)	-0.14 (2.3)	-0.03 (0.13)	-0.007 (0.04)	-0.15 (2.0)
Δoutput						0.14 (1.8)
liability ratio						-0.13 (2.0)
Time dummies	41.4/6 (0.0)	79.4/6 (0.0)	42.0/7 (0.0)	23.3/6 (0.0)	19.5/6 (0.003)	20/6 (0.00)
NT	1567	1567	1829	1567	1829	1567
serial corr(2)	-1.4 (0.16)	-1.4 (0.16)	1.7 (0.10)	-0.55 (0.59)	-1.4 (0.16)	-0.57 (0.57)
Sargan test	68/62 (0.28)	68.2/69 (0.51)	73.4/63 (0.17)	n.a.	n.a.	107/89 (0.09)
LR wage elas	-0.23 (2.3)	-0.27	-0.17	-0.05	-0.06	-0.26
LR capital elas	0.69 (4.3)	1.0 (forced)	0.60	0.46	0.94	0.64

Notes: There are 262 (N) industry-state observations. LR=long run, CRS=constant returns to scale, correct wage=wage per day worked. Instruments for eqns.(1)-(3) are n(2,5), k(2,4), w(2,5), cpi(3,4), $w_s(3,4)$, (*days*-n)(3,4) and time dummies. On notation, see the **Data Appendix**.

just more than a *year* and 90% of the desired adjustment is complete in 3.5 years. A slow rate of employment adjustment is consistent not only with adjustment costs but also with the evidence of insider activity garnered in **Chapter 3**. Consider how rapid employment adjustment in India is relative to other countries for which we have some information.

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where L is the lag operator. The roots (R_1 and R_2) of the quadratic polynomial in (1/L) are +0.52 and -0.33. Thus the speed of employment adjustment is (1-0.52)=0.48. The magnitude of deviations (due to R_2) from the decay path implied by R_1 dampens out over time. Suppose there is a once-and-for-all shock of size Δn in an initial year, when employment is in equilibrium. Then employment in year t can be expressed as

$$n_t = n^* + \Delta n[aR^t_1 + bR^t_2] = n^* + \Delta n\ aR^t_1\ [1 + (b/a)(R_2/R_1)^t])$$

Since $(R_2/R_1) < 1$, $(R_2/R_1)^t \text{-->} 0$ as $t \text{-->} \infty$.

Hamermesh (1993, pp. 253-262) surveys a wide set of estimates of adjustment speeds. Though there is a lot of variation, on average across OECD countries, the median lag is 5.5 *quarters* (p. 253), which is somewhat longer than the half-life of adjustment in India. If both estimates are reliable then it appears that India's job security law, be it exceptionally tight by international standards, does not have effects that are powerful enough to dominate the labour-surplus aspect of the economy.

Unsurprisingly, inertia in adjustment of *person-days* is much smaller than in the adjustment of *persons*. Col. 1 in **Table 8** shows it to be negligible.

The wage elasticity of employment

The current wage rate has no impact on employment. However, there is a well-determined negative coefficient (-0.15) on its first lag. Thus it takes a year for a change in the wage rate to affect employment. This is consistent with restrictions on firing that may lead the firm to trim the work force by natural wastage. It is also suggestive of putty-clay elements in the technology. In both the OLS and WG models, the wage coefficient is close to zero, indicating that the wage is correlated with both the fixed and the idiosyncratic components of the error (θ_{is} and ε_{ist}), so that an estimator designed to deal with these properties of the data is required to identify the true wage effect. Turning to the *worker-days* equation in col.(1) of **Table 8**, we find a negative impact of the *current* wage on employment. This is consistent with the time-scale in which days-adjustment is conducted. Further, consistent with costs of adjustment being greater for workers than for days, the wage has a greater short run impact on days (-0.45) than on employment (-0.15).

With the wage growing at an average rate of 4.2% p.a., a long run elasticity of -0.23 implies a decline in employment at a rate of just less than 1% p.a., other things being held constant. This seriously undermines the World Bank's claim that the wage could account for a decline in employment at the rate of 5.7% p.a. (World Bank, 1989, p.110). In **Section 5.2** we estimate an analogue of the World Bank equation on our data sample, and discuss the conceptual and estimation errors that corrupt their estimate.

Table 8
Employment Equations
DEPENDENT VARIABLE=log(TOTAL DAYS WORKED)
Conditioning on capital and output

Variant/Variable	(1) *GMM: baseline*	(2) *WG*	(3) *GMM: extended*	(4) *(1) with Y, not K*
(dependent variable)$_{-1}$	0.041 (0.8)	0.14 (2.9)	0.059 (1.1)	0.14 (2.3)
(dependent variable)$_{-2}$	0.050 (1.1)	0.07 (2.2)	0.057 (1.3)	0.14 (2.5)
capital stock	0.48 (6.8)	0.34 (5.8)	0.46 (6.7)	
output				0.52 (5.4)
correct wage	-0.45 (2.3)	-0.46 (4.1)	-0.46 (2.5)	-0.66 (3.4)
Δstate output		0.24 (3.1)	0.22 (1.9)	0.02 (0.17)'
Time dummies	14.4/6 (0.03)	20.9/6 (0.00)	15.2/6 (0.02)	3.4/6 (0.75)'
NT (no.observations)	1567	1567	1567	1567
Wald (RHS)	49.1/4	99/5	50.2/5	49/5
serial correlation$_2$	-0.88 (0.38)	-0.74 (0.46)	-1.0 (0.30)	-0.62 (0.54)
Sargan test	80.7/68 (0.14)	n.a.	82/76 (0.30)	76.8/76 (0.45)
LR wage elasticity	-0.49	-0.58	-0.52	-0.92
LR capital elasticity	0.53	0.43	0.52	
LR output elasticity				0.72

Notes: See notes to **Table 7**. Instruments in the GMM equations are: days(2,5), k(2,4), wage(2,5), cpi(3,4), wage$_s$(3,4), (days-n)(2,4), time dummies, and in eqn. (2), Δ(y-p)$_s$. In eqn. (4), k(2,4) is replaced by (y-p)(3,4). In all columns, the Wald joint test on the right hand side (RHS) variables indicates significance at the 1% level. LR=long run.

Returns to scale in production

The long run capital elasticity is 0.69 (s.e.=0.16) which falls short of unity by just less than two standard errors. Thus, constant returns to scale (CRS) can just be accepted with a 95% confidence interval. That WG gives a significantly smaller capital elasticity than GMM suggests that IV is correcting for measurement error in capital stock to some extent. To investigate returns to scale we run the following transform of the baseline model:

$$n-k = \lambda_1(n-k)_{-1} + \lambda_2(n-k)_{-2} + \beta_1 k + \beta_2 w + \theta_t + \theta_{is} + \varepsilon \qquad (9)$$

The Wald test of the CRS restriction is -2.0 (t-statistic on β_1), implying decreasing returns though not by a huge margin. If the capital coefficient is underestimated inspite of IV, it may be argued that CRS should be imposed even if it is statistically rejected. Forcing the long run capital coefficient to be unity gives col.2 in **Table 7**. The long run wage elasticity is larger, but the difference is not significant. As it makes little difference either way, the capital coefficient is left unrestricted. In **Chapter 5**, the question of returns to scale is taken up directly in the context of a production function.

Time dummies or macroeconomic effects on employment

The time dummies are jointly highly significant. Of the individual year coefficients, it is only 1987 that is significantly different from the base year, 1982, from which its deviation is positive. Indeed, the data describe a significant pick-up in employment growth in 1987. Data for 1988 and 1989 have recently become available. Although the analysis does not incorporate these data, they are examined to check whether the upturn in employment was sustained and it does seem to have been. This turnaround guides discrimination between the alternative hypotheses regarding the 1980s experience that are discussed in **Section 6.** Regressing the time dummy coefficients on trend yields an average coefficient of -0.027 and the associated R-square is 0.84 (sample=1982-1986). Thus the sum of aggregate influences on employment can account for a decline in employment at the rate of 4.2% p.a.

We now digress briefly to explain how we have arrived at the figure of 4.2% p.a. The baseline employment model may be written in levels as:

$$(1-\lambda_1-\lambda_2)n = \theta_1 k + \theta_2 w + \theta_t + \theta_{is} + \varepsilon \tag{10a}$$

where θ_t are time dummies. If t is a time trend, then taking the dot product of each variable with t and dividing through by t.t, this can be transformed to a model in growth rates:

$$(1-\lambda_1-\lambda_2)n^* = \theta_1 k^* + \theta_2 w^* + \theta^*_t + \theta^*_{is} + \varepsilon^*, \tag{10b}$$

where x^* is the growth rate of x. The growth term in the fixed effects (θ^*_{is}) is zero. The growth term in the time dummies (θ^*_t) is obtained by regressing the time dummy coefficients on a linear trend. Since the equation is estimated in first-differences, the observed time dummy coefficients (D_t) are not the θ_t of the levels model. Rather, D_{83}=[(θ_{83}-

$\theta_{82})-(\theta_{82}-\theta_{81})]$, $D_{84}=[(\theta_{84}-\theta_{83})-(\theta_{82}-\theta_{81})]$, and so on, where the equation constant is $(\theta_{82}-\theta_{81})$. We add the constant to each dummy coefficient to get a growth effect for each period. Either these growth effects can be averaged, or setting $\theta_{81}=0$, each θ_t (t=1982-1987) can be retrieved and the series regressed on a trend. We adopt the latter method. The resulting growth rate (0.027) is divided by $(1-\lambda_1-\lambda_2)$ to yield the figure of 4.2% p.a.

Taking stock

The GMM estimate of the capital elasticity implies that, ceteris paribus, capital accumulation at 7% p.a. over our sample period implies employment growth at the rate of 4.8% p.a. So, together, the product wage, the capital stock and the sum of aggregate influences gathered in the time dummy coefficients predict a fall in factory employment at the rate of 0.6% p.a., which closely matches the observed rate of decline of 0.3% p.a.

The Extended Model

We now discuss other variables in the model. Results of a pruned extended model are in column (6), **Table 7**. **(i)** The realized change in real industry output (Δy_{it}), a proxy for changes in exogenous demand (σ^e), acquires a positive and weakly significant coefficient. This indicates that the mark-up is counter-cyclical, which is consistent with existing research (see Chatterji, 1989). In fact the degree of imperfect competition varies substantially across industries, and some are more sensitive to agricultural prices than others. So we re-estimated the equation allowing industry-specific coefficients on Δy_{it}. The 18 interaction terms are jointly significant and there are significant differences between them. Industry-wide changes in demand have a positive impact on employment in cotton textiles, basic metals and electricity generation, and a negative impact in chemical products and wool & silk textiles. There is no indication of imperfect competition in the remaining industries. The overall weight of the evidence is that there is a tendency for employment to respond positively to cyclical movements in demand, but that there are wide differences in the response coefficients of the different industries. Therefore the coefficient of 0.14 estimated under the restriction of common slopes must be regarded as too fragile to yield any firm conclusions. **(ii)** The alternative wage, w^a_{st}, is insignificant, suggesting that even if efficiency wage mechanisms do count, this is not the way to identify them. We experimented with inclusion of the relative consumption wage, as well as direct inclusion of the price wedge but these effects are poorly determined and finding valid instruments that will out-perform lags of the included variables proved difficult. **(iii)** The *loan-capital ratio* has a negative impact on employment. While we do not want to read too much into this industry-level result, it may inspire further research. **(iv)** The data do not support the inclusion of industry and state trends ($\theta_i t$ and $\theta_s t$). It appears from our investigations that, together, n_{t-2} and θ_t mop up the variation described by heterogeneous trends. They are preferred as they yield a more parsimonious specification. **(v)** In the baseline model, technical progress (ΔA) is expected to be captured by the time dummies. Industry-time dummies (θ_{it}) were included to see if the equation parameters change once technical progress is more completely controlled for. As there was no significant change[18] and they consume more than 100 degrees of freedom, the θ_{it} were not retained even though they were jointly significant at 1%. An alternative characterization of TFPG is the modified Solow index (Δtfp_{ist}). It had virtually no effect on employment (coefficient=0.01, t=0.45), not even if the time dummies were dropped. Hence the evidence is ambiguous on the question of whether, *ceteris paribus*, technical progress has destroyed jobs. Since, overall, the data reject the modifications, we stick with the baseline equation.

5.2. The Output-Constrained Employment Model

Dominant among the scarce body of analyses of the 1980s slowdown in India's factory employment growth is a contribution by the World Bank (1989) (**Section 2**). This estimates the wage elasticity at -0.82 and claims that, *ceteris paribus,* wage growth could account for a decline in employment of 5.7% p.a. On this basis, the acceleration in wages in the 1980s is proposed as *the* explanation of the employment slowdown. The capital-model yields a wage elasticity of -0.23, implying that, *ceteris paribus*, the wage can account for a decline in employment of at most 1% p.a. Since the World Bank estimates an output-constrained

[18] The one change is that the wage is rendered only marginally significant. Since the model is overfitted, this is not pursued.

model, the two sets of estimates are, strictly, not comparable. However since, by theory, the output-constrained model has a *smaller* wage elasticity than the 'capital model' (**Appendix 4.1**, footnote 2), it is even more odd than otherwise that the Bank gets such a high wage coefficient. In this section, we investigate why the World Bank's estimates diverge from ours. We first estimate an exact analogue of their equation for our sample period, which is more representative of the 1980s than theirs. Using this as a benchmark, we then incorporate various modifications, arguing that the Bank's equation is mis-specified. A 'correct' version of their model yields a small wage elasticity, similar to that obtained in the previous section.

Analogue of the World Bank equation: Change in sample period

Refer **Table 9**. The Bank estimates an employment model by within-groups on an industry-year panel spanning *1974-1984* (column 1). An *identical* equation (column 2) is estimated on our data sample, which differs in including a regional dimension and in that it covers the period *1979-1987*. As our sample is confined to the 1980s, the elasticities in (2) are more relevant to discussion of employment growth in the 1980s. In fact it is rather careless of the Bank to make the case that higher wage growth in the 1980s as compared with the 1970s explains the 1980s employment decline, when more than half their observations pertain to the 1970s[19]. They did not explore the temporal stability of their parameter estimates. Comparison of (2) with (1) indicates changes in the structural parameters as time progresses forward from the mid-1970s. The long run earnings elasticity is down from -0.82 to -0.39. It appears that employment was *less* sensitive to earnings in the 80s than in the 70s. Given the overlap of periods in the data this is not conclusive but it does suggest that labour costs are unlikely to have been a central explanation of the *deceleration* in employment from the 1970s to the 1980s. One reason to expect a lower wage elasticity in the 1980s is that, in this decade, there was an increasing tendency for wage bargains to be linked to productivity (Davala, 1994). The point estimates on earnings and output are not significantly different between the two periods, rather, the inertia coefficient is much smaller in the later period. In fact, the Goldar (1987) equation reported in **Section 2** shows that going back further in

[19] Wages only began to accelerate in 1981, and employment only began to decline in 1982.

time (1960-1977), employment inertia is even greater. Either there is an estimation problem somewhere, or the inertia parameter is unstable over time.

Table 9
Employment Equations
THE CONSTRAINED-OUTPUT MODEL
Dependent variable=ln(workers)

	(1) WG	(2) WG	(3) WG	(4) WG	(5) WG	(6) WG	(7)GMM
Variant/ Variable	*World Bank*	*Exact analogue*	*Correct wage*	*Correct $wage_{-1}$*	*Add n_{-2}*	*Add θ_t*	*IV*
$(dep.var)_{-1}$	0.55 (12.0)	0.23 (4.4)	0.24 (4.5)	0.24 (4.6)	0.23 (3.5)	0.24 (3.7)	0.26 (3.1)
$(dep.var)_{-2}$					0.14 (2.9)	0.14 (3.1)	0.16 (3.7)
output	0.31 (8.4)	0.30 (7.1)	0.26 (6.5)	0.26 (6.7)	0.25 (5.3)	0.26 (5.1)	0.63 (4.9)
$output_{-1}$							
earnings	-0.37 (7.3)	-0.30 (3.6)					
correct wage			-0.06(1.6)				
correct $wage_{-1}$				-0.097 (3.0)	-0.114 (3.1)	-0.095 (2.4)	-0.15 (1.8)
Time dummies	no	no	no	no	no	14/6 (0.03)	20/6 (0.0)
NT	198	1829	1829	1829	1567	1567	1567
serial corr(2)		1.8 (0.08)	1.8 (0.07)	1.8(0.08)	-0.3 (0.77)	-0.3 (0.74)	-1.7(0.08)
Sargan test							49.5/44 (0.26)
Wald (RHS)		63.9/3	58.8/3	57/3	111/4	87.3/4	58.2/4
LR wage elas	-0.82	-0.39	-0.079	-0.128	-0.18	-0.15	-0.26(1.6)
LR Y elas.	0.69	0.39	0.34	0.34	0.40	0.42	1.1 (3.4)

Notes: See notes to **Table 7**. Col. (1) presents estimates obtained by the World Bank (1989) for the period 1974-1984. Equations (2)-(5) develop our analogue of this equation, estimated on data covering the period 1979-87. In (1), the standard errors are not heteroskedasticity- consistent. Instruments in the GMM equation are: n(2,5), w(2,5), y(3,5) and time dummies.

An estimation issue of possible relevance is that within-groups estimates of autoregressive coefficients incorporate a downward bias of the order of 1/T, where T is the time-dimension of the panel. This could, in principle, explain the different estimates of employment inertia since our sample (T=9) is shorter than that of the Bank (T=11) which, in turn, is shorter than that of Goldar (T=18). However it seems unlikely that a difference in bias of 0.02 [(1/9)-(1/11)] can reconcile our coefficient of 0.24 with the Bank's 0.55, which is almost four standard errors larger. To confirm this, we have re-estimated the equation in column

(2), using GMM to get the 'true' autoregressive parameter in 1979-87:

$$n = 0.02 + 0.305n_{-1} + 0.68y - 1.09(\text{earnings})$$
$$(2.4)\ (2.2)\qquad (5.3)\ (5.4) \qquad\qquad (11)$$

If 0.31 is the correct autoregressive coefficient and, with T=11, the Bank's WG estimate of 0.55 is *downward* biased, then what we are looking at appears to be a 'structural break' in this parameter. This is an important finding in itself. It is not inconsistent with structural changes in the industrial sector in the 1980s. In **Section 6.3**, we report evidence of increased subcontracting and, related, the relative growth of small firms. We may also speculate that adjustment is facilitated by buoyant output growth and a competitive environment, both of which characterized the 80s. Finally, with several thousand recently unemployed factory workers available, hiring costs will have been lower than in a time when fresh recruits included recently arrived migrants. To the extent that employment inertia reflects adjustment costs, the decline in inertia encourages skepticism of the view that the extension of job security in 1982 was responsible for the employment decline. This view is discussed further in **Section 6.2.**

Modifying the World Bank's specification

Flaws in the Bank's equation

The obvious flaw in the World Bank's model (column 1, **Table 9**) is that the variable regarded as the wage is in fact real annual earnings per worker. Goldar (1987) makes the same mistake. Implicit in this usage is the assumption that the actual labour input per worker is constant. In fact, there was significant trend growth of 1.7% p.a. in average days worked per worker (or *days*), and considerable inter-industry variation (see **Table 1**). In addition, there was a significant break in TFPG in 1982 (Ahluwalia (1991), for example). We propose that this is to some extent due to an increase in *(unobservable) effort* on the part of workers, possibly caused by the progressive dismantling of industrial protection mechanisms in the 1980s (**Section 6.4**). Neglect of these trends in labour utilization results in a biased view of the role played by wages. Not only is the earnings elasticity higher than the wage elasticity ("β"), but the growth rate of earnings is also greater than the growth rate of wages ("Δx"). In our estimates, we control for variation in both *days* and *unobservable effort*. In addition, unrestricted *lag structures* are allowed on all variables and an *instrumental variables* estimator is employed[20]. The sum of these influences yields estimates that are significantly different from those obtained by the Bank. We have experimented with altering the sequence in which the changes are introduced, but there is nothing exceptional to report.

Following an Evolution of the Equation

In column (3), **Table 9**, real annual earnings per worker is replaced by the wage *per day worked*[21] (Tables: the '*correct wage*'). This makes a dramatic difference. The wage elasticity is -0.08, compared with an earnings elasticity of -0.39 in col. 2. In the capital-model, it was the *lagged* wage that influenced employment. So in column (4) we report the (pruned) results of allowing lags of the wage in the model. The lagged wage is significant with an elasticity of -0.13, and the current wage falls out. We subsequently estimate a general distributed lag model. The *second lag on employment* is significant, which probably reflects heterogeneity in adjustment costs among workers. The wage elasticity is now -0.18. (col. 5). In col. (6), *time dummies* are included in the model. These control for all aggregate variation in the data *including* changes in competition and common gains in effort and efficiency. The wage elasticity is brushed down to -0.15. Not only the World Bank but most investigators of labour demand treat the wage as an exogenous variable in the employment equation. But it is unlikely that shocks to employment will have no effect on wages. So, col. (7) reports the equation in (6) re-estimated by GMM, using *instruments* for each of the three

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[20] With reference to our investigation of employment conditioned on capital, we may expect these changes to *raise* the wage elasticity, making the Bank's findings appear even more mysterious. Allowing unrestricted lags increased our estimates of employment inertia and raised the long run elasticities (compare col. 1 and 3 in **Table 7**), and instrumenting the wage made its coefficient larger in absolute terms (col. 4 and 1 in **Table 7**).

[21] Note that: (a) This is not the same as the wage *per working day*. Not all working days in the year are actually worked on account of prevalent absenteeism, strikes and lockouts; and (b) Strictly speaking we are only replacing annual earnings with daily earnings. However, since *days* are standardized as 8 hours, our measure is much closer than earnings to the concept of a wage rate.

explanatory variables. The wage and the autoregressive coefficients increase and the long run wage elasticity is almost doubled (-0.26)[22]. It is also worth noting that the output coefficient only becomes sensible once it is instrumented.

According to this, the final model, if output and other factors are held constant, then trend growth in the wage of 4.2% p.a. over the sample period can explain a decline in employment at the rate of 1.1% p.a. This is again substantially smaller than the 5.7% p.a. decline claimed by the Bank.

6. UNDERNEATH THE NUMBERS

Have we located the sources from which disincentives to employment growth were emanating in the 1980s and what are the main issues that have arisen in this investigation? Estimates of the employment models in the preceding section showed that aggregate factors encapsulated in the time dummies played a significant role in depressing employment. Therefore a hypothesis such as that there were special circumstances in the food processing and textile sectors, true as it may be, is not a sufficient explanation of the 1980s employment record[23]. In this section, we consider some hypotheses that appear consistent with an across-the-board deceleration in employment.

Investigation of the wage elasticity brought into view the fact that annual days worked per worker (or *days*) showed a significant trend increase in the 1980s in all but 4 of the 18 industry-groups (**Table 2**). It appears that, compared with preceding decades, some force came into play in the 1980s that led employers to fuel increased production with an increase

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[22] The wage elasticity in the capital-model should be $[\sigma_{LK}/(1-\alpha)]$ and that in the output-constrained model should be σ_{LK}. If $(1-\alpha)=0.3$ (**Chapter 5**), then the former model should yield an elasticity that is thrice as large as that estimated from the latter model, which it doesn't. On the other hand, there is a large amount of sampling variation and the standard errors of both estimates suggest that our estimates are not inconsistent with what the theory predicts.

[23] **Table 2** shows that the decline in employment was largest in the food and textile sectors.

in days worked, rather than workers. There are at least four possibilities here[24]. One is that additional workers, unlike additional days, are associated with a *fixed cost,* which increased in the 1980s. However, we are not aware of such a change. It may be argued that the extension of job protection to smaller firms meant an increase in fixed costs for them. Our skepticism regarding this view is elaborated in **Section 6.2.** The second is that the permanence of the upturn in production in the early 1980s was uncertain. If so, it would have been rational for employers to adjust *days* rather than workers, given lower adjustment costs for days-adjustments (evidence of which is in **Section 5.1**). The third is that by the early 1980s, deregulation and liberalization had proceeded far enough to have significantly increased the competitive pressures faced by manufacturing firms. A substitution of time-worked for workers was an efficiency-raising response to this pressure. Finally, the growth in *days* may simply reflect a recuperation of time lost on account of work stoppages. We suggest that improvements in public infrastructure can explain this to a fair extent. These arguments are discussed in **Section 6.4**. Other explanations that may contribute but are denied a central role in explaining declining employment in the 80s are: increased subcontracting, the substitution of casual for regular workers, acceleration in the product wage, the job security amendment of 1982, and changes in the output-composition of manufacturing.

6.1. The product wage was growing too rapidly

The extent to which rising product wages are to be blamed for the decline in employment was taken up as the central issue. Our investigations suggest that while wage growth in itself would have caused a small employment decline, allowing for the growth in capital stock or output leads us to expect robust employment growth.

We estimate the wage elasticity of employment to be about -0.23, which is quite small. To some extent, this must reflect the low price elasticity of product demand, a feature of imperfectly competitive product markets. The argument that wage growth has been a major

[24] It is completely meaningless to think of the substitution of days for workers as being because wages are too high. Worker-days are paid for just like workers are paid for (see Section 3, **Chapter 3**).

employment deterrent in Indian manufacturing stems from the view that high wages result in a rise in the capital intensity of production (eg. Ahluwalia, 1991:82-83 and World Bank, 1989:108). In fact, rising capital intensity at constant wages can be explained by investment subsidies implied by certain policies, of which the two most important are (1) asset-based tax incentive schemes such as development rebate and initial depreciation allowance, and (2) liberal grant of loan capital and other investible funds by public sector financial institutions at relatively cheap rates of interest (Goldar, 1983). In fact, rising capital intensity may be the cause and not the effect of rising wages (see **Chapter 3**). Any claim that causality runs the other way presupposes technologies that exhibit a high elasticity of factor substitution. Although there are no reliable econometric estimates of this for India, the evidence suggests that in developing countries as a group, the elasticity lies in the region of 0.3 to 0.5 (Gillis, 1987). In the 1980s, industrial composition changed in favour of process industries in which the capital-labour ratio is particularly rigid (Kelkar and Kumar, 1990). Furthermore, capital intensity grew no more rapidly in the 1970s, when there was little wage growth, than in the 1980s when wages accelerated. The fact that capital intensity was nevertheless growing quite fast in the 1980s can be accounted for by increases in work intensity and effort that raise the marginal productivity of capital. This shifts the emphasis away from the wage as a causal factor. There is also evidence from a World Bank survey of Indian firms that, in some industries (eg., soap), the degree of mechanization is related to product quality more than to wage differentials (see Mazumdar 1988, p.236). Finally, if labour was becoming more expensive, so was capital. In response to the public sector borrowing requirement on the one hand, and policy directives of priority sector lending on the other, the cost of credit for the private non-agricultural sector seems to have increased significantly in the 1980s[25].

[25] Interest costs as a proportion of value added rose steadily from 1979 onwards (data in Chandhok *et al*, 1990). The (deflated) rate on deposits of one year or more offered by scheduled commercial banks has also risen in the 1980s, there having been a specially sharp upward spike in 1979 (Nagaraj (1994), Figure 11; Source: RBI Bulletin, various issues).

6.2. Pro-labour policies

The World Bank (1989) ascribes the 1980s employment decline to wage growth, and ascribes wage growth to institutional push factors. Lucas (1988 and 1993, with Fallon) too, is a keen proponent of the view that unionism and job security have caused excessive wage increases. In **Chapter 3**, we have argued that these institutional factors are not fundamental to wage determination in India, though they probably contribute. For instance, the share of independent internal unionism increased in the 1970s, especially after 1975 and this is expected to increase wage push (eg.,Bhattacharjee 1987). In a related argument, we have contested the notion that wages have grown excessively (subject, of course, to the notion being ill-defined). Labour costs rose from an anaemic 2% p.a. in the 1970s (**Table 6**) to a healthy 5.6% (**Table 3**) in the 1980s. This can be explained by an acceleration in productivity and work intensity and by the fact that consumer prices began, in this decade, to grow faster than manufacturing prices[26]. **Table 4.3, Chapter 3** shows that these variables can account for, on average, more than 90% of the temporal variation in nominal earnings in the 1980s. In view of the *surprise* generated by factory wage behaviour in this decade (eg., Ahluwalia 1991, p.83), it bears mention that agricultural wages also accelerated after the mid-1970s (Jose, 1988 and Acharya and Papanek, 1989). In any case, the World Bank-Lucas view is void if the bite of legislation and unions was weakened in the 1980s, which is what we now propose. In addition to pushing wages, industrial and labour policies in India are deemed to have created direct disincentives to employment growth. The two aspects underlined by the Bank are (i)"dysfunctional" labour relations and (ii) restrictions against retrenchment and closure.

While factory sector unions probably have profound, if complicated, effects on the numbers of factory workers, there is little reason to believe that they had greater influence in the

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[26] Nominal wage growth follows the consumer price index, in which food items have a weight of about 80%. If workers are to simply maintain their real wages, then the recipe for checking industrial wage inflation is to invest in agricultural development, especially irrigation. A short term strategy is to control agricultural prices, which was done until the early 1990s. The recent liberalization of agricultural commodity prices will further push nominal wage growth. At the same time, increasing competition in the market for manufactures is likely to contain the growth of manufactured goods prices.

1980s than before. Evidence has been accumulating to the effect that *industrial relations* were becoming increasingly progressive (Ramaswamy 1988, Davala 1994) and that union power was declining (Datt 1993, Nagaraj 1994) during the 1980s. Union density fell from 45% in the late 1970s to 30% towards the end of the 1980s, and while the proportion of worker-days lost in disputes fluctuated without a trend in 1970-89, the number of workers involved in disputes fell from more than 38% in 1973 to less than 10% in 1988[27]. Possibly a sharper indicator of a shift in bargaining power, the ratio of lockouts to strikes was on the increase (Labour Bureau, 1987). In the next section we catalogue evidence of an increase in subcontracting, and the proportion of small firms in manufacturing. The first threatens the power of unions in parent firms (in the factory sector) and the second directly implies that a shrinking fraction of the registered sector is subject to both unionism and the law[28]. One may argue that, in the face of greater competition in the 1980s, unionism became a 'binding constraint' but this must be distinguished from the claim that it caused the employment decline. Thus the Bank's first claim stands contradicted.

Regarding the second, *job protection* is expected to reduce both firing and hiring. Therefore, in principle, its impact on employment is ambiguous. To the extent that wage push is greater when there is no threat of layoff, there may be an indirect negative impact on employment, but this will show up in the wage coefficient. Using data for the census sector (50/100$^+$ workers: see **Data Appendix**) of Indian firms, Fallon and Lucas (1993) find that institution of the job security provision in 1976 resulted in a 17.5% drop in the long run demand for labour at *given* output levels[29]. While the law initially applied to establishments with more

[27] In 1985, 22% of all industrial disputes were initiated for 'personnel and retrenchment' reasons, a similar percentage for 'wages and allowances', 16% for 'indiscipline and violence', 7% pertained to the determination of 'bonus' and 1.8% were on account of 'leave and hours of work'. Of the residual 28% were for a variety of other reasons and only 3% for unknown causes. There are data for 1976-1986 and the distribution of disputes by causes appears to have been quite stable over this period (Labour Bureau 1987, Table 2.13).

[28] Small firms (less than 100 workers) are explicitly exempt from certain regulations (such as the job security law). Unions tend to be less powerful in smaller firms (Verma 1970, Deshpande 1992:p.95).

[29] The magnitude of the employment decline that they propose encourages skepticism of their results as it implies an enormous increase in productivity, which was not observed in the period 1976-1982.

than 300 employees, in 1982 its scope was extended so as to cover establishments with more than 100 employees[30]. As it was in 1982 that total employment began to decline significantly, it is tempting to draw a causal connection. We do not have the data to investigate the question directly but there are grounds for skepticism. First, the disaggregate data (**Table 2**) show that the decline in employment began before 1982 in some sectors, having started in Cotton Textiles in 1979. Second, there is evasion of this law (eg., Mathur 1989, Deshpande 1992, Papola, 1992) and it is more likely in the traditional industries[31]. But as it is in the traditional industries that the decline was concentrated, this legal constraint cannot be *the* explanation of the employment decline. Moreover, deregulation in the product market, the apparent decline in union power, and the new liberal outlook of the government are together likely to have contributed to looser enforcement of the law in the 1980s. Also, in **Chapter 2**, we found evidence that unemployment depresses wage. If workers faced *no* threat of layoff, this effect would be difficult to reconcile with the theory. Third, the provision was extended to smaller establishments (100-300 workers) but the evidence suggests that these were gaining in employment share (Chandhok *et al*, 1990). It is striking that while employment growth was negative in firms with more than 1000 workers, it was positive in firms smaller than this. Further evidence is in **Section 6.3**.

Fallon and Lucas found no impact of the 1976 law on the *speed* of employment adjustment, and we too find no evidence of increased employment inertia consequent upon extension of coverage to smaller firms in 1982 (compare col. 1 & 2 in **Table 9**). This is relevant because job security provisions are probably as likely to impact on the speed of employment

[30] The size range of *100-300 employees* that was encompassed by the law in 1982, includes just less than 7% of all factories and just more than 15% of all employees in the registered sector. In the period 1976-1982, only 52% of factory workers, employed in 4% of all establishments, were covered by job security provisions (>*300 employees*); and by the extension in 1982, the proportion of employees covered rose to 72% and the proportion of establishments, to 11% (>*100 employees*). (All figures relate to 1986 and are drawn from the ASI).

[31] There is less incentive to evade the law in the modern industries such as those producing electrical machinery and petroleum products because returns to a stable, skilled and well-paid work-force are relatively high. Also, the modern industries tend to have larger firms. Evasion is harder for large employers, especially among the big family-houses because they cannot escape the eye of the state and they have reputations to protect. This is a reason why *size* may affect wages (**Chapter 3**).

adjustment, as on the level of labour demand.

That job security has a negative impact on employment is a popularly held view that holds sway in top levels of the Indian government and any contention of it is of immediate policy importance. For example, a document on the direction of the current economic reforms says, "..we must review and reform the current legislations for employment and industrial disputes to ensure that excessive rigidities are removed and long-term growth facilitated. ...Rigid rules limiting the flexibility with which labour can be hired and retrenched have the effect of pushing entrepreneurs into more capital-intensive technology and reduce the number of workers they have to deal with" (Government of India (1993), p.34). Although we think that the 1982 amendment to job security provisions was not a central cause of the employment slowdown, it is quite possible that it contributed to increasing casualization and subcontracting, and to the growth of firms with less than 100 employees.

6.3. Illusory, or A shift in the size structure of employment

The hypothesis is that job losses in larger firms were, to some extent, compensated by job gains in smaller firms, which are not counted in our factory sector data (sector definitions in **Data Appendix**). If this is true, then the true employment picture for the 1980s decade may not be as bleak as our data suggest.

What is the evidence? During 1973-87, employment grew at a rate of less than 1.5% p.a. in registered manufacturing, and at 4.6% p.a. in unregistered manufacturing (Papola 1992, p.37). Thus the employment share of the latter rose, from 70% in 1977 to 77% in 1987 (NSS, various issues; rural+urban). Following liberalization of licensing requirements in the 1980s, even some of the larger firms may have evaded registration. Further, Nagaraj (1984, p. 1445) has pointed to a general tendency among *registered* firms, for small ones to under-report employment. Employment growth in the 1980s was positive in factories with less than 1000 workers and negative in larger ones. The number of workers per factory has declined for the last three decades in almost all industries (**Table 10**). These facts denote a size shift in employment in favour of smaller firms. In support of the size-shift hypothesis, it is observed that industries which suffered the largest decline in employment growth generally had a relatively rapid expansion of their smaller firms (eg.,**Table 10**).

Why did the proportion of small firms grow? The size-shift seems to have been stimulated by *trade liberalization*, *policies designed to encourage small firms*, and a *growth in subcontracting*. The largely export-oriented electronics, leather, jewellery and food processing industries have a concentration of small firms. As for policy, the official definition of the small scale sector has been revised to bring an increasing number of firms within its scope and product reservations for this sector have been increasing. In 1965, the

Table 10
AVERAGE FACTORY SIZE BY INDUSTRY
Number of workers per factory

Industry	1973	1979	1987	Industry	1973	1979	1987
Food products	42	54	43	Petroleum & rub	49	39	35
Beverages & tob	85	37	50	Chemical products	77	62	57
Cotton textiles	160	138	107	Cement, glass etc	63	45	40
Wool & silk tex	56	53	81	Basic metals	85	75	78
Jute textiles	575	919	760	Metal products	32	25	24
Textile products	33	29	34	Non-elec machinery	51	42	39
Wood & furniture	21	17	17	Electrical machinery	76	65	58
Paper & printing	52	44	43	Transport equipment	192	127	110
Leather products	63	57	60	Other products	32	26	33
				Electricity	n.a.	2153	3423

Notes and sources: Author's calculations based on ASI data (CSO), 'Summary results for the factory sector', for 1979 and 1987. The ASI data for 1973 are drawn from Chandhok *et al* (1990).

reserved list had about 45 items. In 1973, it had 123 and in 1982, more than 800 (Nagaraj, 1984). Subcontracting raises labour productivity as it typically involves keeping the high value added jobs in the parent firm and farming out the labour-intensive ones. If subcontracting did grow significantly in the 1980s, then it is a nice explanation of both the deceleration in employment and the acceleration in productivity[32].

[32] However, rapid growth in subcontracting in the 1980s implies that the structural parameters of the employment-output relationship may have been changing. In that case, an employment function estimated

Subcontracting may be expected to be attractive to Indian firms, with segmentation of the labour market implying that small firms face lower labour costs[33], while large firms tend to have advantages in marketing and in procurement of raw materials. Potential gains from subcontracting appear to have been reinforced by various allowances for small firms, especially since the early 1980s. For example, small firms can get credit on concessionary terms[34] and to avail of the benefits of export houses set up in the early 1980s, a large firm has to show the government that part of its production is in the small sector. Wider changes in the policy framework in the 1980s (**Section 6.4**) probably encouraged subcontracting as well. Competition raises the pressure to cut costs, and subcontracting is one ready means of doing this. Import liberalization in the 80s led to rapid growth in industries (especially electronics) which concentrate on assembly of imported goods (Kelkar and Kumar, 1990)[35] and assembly work is typically subcontracted. Further, spurts of reform increased uncertainty. Subcontracting offers parent firms the option of passing the impact of demand fluctuations onto smaller firms that are able to operate with greater flexibility, especially as regards employment adjustment. Given restrictions on mill loomage, mills in the factory sector subcontracted the weaving of yarn to powerlooms (Desai, 1981b) and this tendency was, very likely, reinforced by the long and painful textile mill strike of 1982-83. (Textile mills employed about 20% of factory workers in 1978). Nagaraj (1985) notes that subcontracting accelerated in the 1970s. It may be argued that, by the 1980s, large-small firm linkages had matured and skill-diffusion among small firms had advanced sufficiently.

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on 1980s data is likely to be unstable. The use of disaggregate (as opposed to aggregate time series) data limits the problem though it probably does not overcome it.

[33] Field studies that confirm that small firms pay lower wages and are exempt from labour regulations include Lall (1980), NSIC (undated), Harriss (1982) and Papola and Mathur (1979). The small sector may offer large firms special skills along with lower wages. Based on a field study in Coimbatore in Tamil Nadu, Harriss (1982) notes that often, and especially in foundries, large firms subcontracted out production so as to use the specialized knowledge and skills of small firms.

[34] A substantial fraction of suppliers to *Escorts Ltd*, a large engineering firm, are small firms, from whom it takes a months credit. As it sells against cash, this firm uses ancillarisation as a strategy for generating investment funds, which, it claims, afford it huge savings on interest payments (*India Today*, 1982).

[35] Prominent examples are computers and consumer durable goods. This was significant enough to have earned the 1980s growth-recovery the 'bad name' of import-led growth.

The relatively rapid development of infrastructure in the 1980s (Section 2.1, **Chapter 5**) no doubt contributed.

Another important change in work force structure was an increase in the proportion of *casual workers*. Thus, in the census sector, the share of casual workers more than doubled from 4.6% in 1980 to 10% in 1986 (ASI, 1991). This is relevant because, although casual workers are supposed to be counted in the ASI statistics, they are probably under-counted in an annual survey.

Although we have woven together considerable qualitative support for the size-shift hypothesis, it has an important limitation. If it were the main explanation, then employment gains from healthy output growth in the 1980s would have shown up as a sizeable increase in employment in the unregistered sector. In fact, there was a distinct slowdown of employment growth in the 1980s in the *entire* manufacturing sector. It was 5.1% in 1972-77, 3.8% in 1977-83 and 2.1% in 1983-1987 (Planning Commission, 1990; based on NSS data). Since the NSS covers firms of all sizes, there is no question of under-counting small-firm employment. There is also direct evidence of a decline in employment growth in *unregistered* manufacturing from 4.6% in 1973-87 to 2.8% in 1983-87 (The corresponding figures for registered manufacturing are 1.4% and 0.06%, from NSS sources). Employment growth in small enterprises was evidently not sufficient to counter-balance the slowdown in factory employment, and in neither large nor small firms was the acceleration in output reflected in employment[36]. To the extent that there was some counter-balancing, there was growth in *bad jobs* as against *good jobs*[37]. This is significant because, in India, the *quality*

[36] Ahluwalia (1991, pp.84-85) favours an explanation of the observed decline in employment in terms rising wages in factories and a transfer of employment to the non-factory sector (hypotheses 6.1-6.3). However, she demonstrates insight in remarking that this is only a part of the whole story, 'larger explanations' having to be sought in 'the overall macro and micro policy environment facing the organized manufacturing sector'. She does not pursue this. In the following section, we turn to a 'larger explanation'.

[37] Though we are directly concerned with manufacturing, a reduced supply of *good jobs* is reflected in the following Planning Commission statistics for employment growth in the entire organized sector, including services, plantations etc. in addition to manufacturing: 1973-77=2.5% p.a, 1977-87=2.4% p.a. and 1983-87=1.4% p.a.

of employment is as important a measure of 'well-being' as is its *quantity*.

6.4. Higher effort: dehoarding, recuperation of lost time and efficiency wages[38]

Deregulation started in 1979 with the return of the Congress (I) to power. In 1981, India went to the IMF for an EFF (Sengupta, 1995) and brought home the decision to tighten the budget constraints of all agents in the economy. In 1984, Rajiv Gandhi came to power, and started consolidating the reforms. Thus domestic deregulation and trade liberalization made significant progress in the 1980s (see Kelkar and Kumar (1990) for details of the changes instituted). Since regulation pertained primarily to the registered sector, one would expect the impact of this progression to be felt most acutely in this sector. An evident impact of these changes was increased competition, especially from internal but also from external sources. There exist myriad indicators of a competition shock. For example, profitability in the private sector declined through the 1980s (Nagaraj, 1990). There was a higher incidence of 'industrial sickness', marking out the losers in the competition. Data from the Chief Inspector of Factories in Bombay show that the the proportion of closed factories in the registered sector was 9.5% in 1981 and 12% in 1989. For most survivors, there was a marked acceleration in total factor productivity (**Chapter 5**).

Our hypothesis is, partly, that competition induced a cost consciousness that protection had formerly obscured. This forced firms to strengthen financial discipline and efficiency. This is clearly something that distinguishes the 1980s from the 1970s and we speculate that aspects of efficiency underlie the time dummy effects in the estimated equation. Several authors have commented on inefficiency in Indian industry being an outcome of excessive protection (eg., Bhagwati and Desai 1970, Bhagwati and Srinivasan 1975, Ghosh 1982 and Ahluwalia 1985). Given an inheritance of excess employment from the previous decade, an easy way of cutting costs was to shed labour, or at least to stop hiring and allow the work force to shrink by natural wastage. Natural wastage in this period may have been significant, given that a large number of people hired in the first thrust of industrial planning in the

[38] For a summary of the central hypotheses and a development of some of the ideas set out here, see Section 2.3.3, **Chapter 5**.

1950s and 1960s would have reached retirement age in the 1980s. The loss was compensated by an increase in working time and greater effort on the part of formerly *hoarded labour*. This is probably related to the rise in productivity-bargaining in this decade (Bhattacharjee, 1987). The choice of increased working time over increased employment was probably reinforced by increased uncertainty in the 1980s. This is likely to have arisen from the fact that the reforms were *ad hoc* and came in spurts through the 1980s, being continuously threatened by rumblings in the politico-economic structure. The hypothesis gains support from evidence of trend increases in the 1980s in both annual days worked per worker (or *days*) and efficiency (refer **Chapter 5**).

To some extent, the growth in *days* is probably the result of less production time being lost, rather than the result of a *decision* to dehoard. *Less time lost* because of disputes, machine breakdowns and material shortages may ultimately be ascribed to increased competition and import-liberalization respectively. However, recuperation of time lost on account of power (and, again, material shortages)[39] is the result of increased public investment in infrastructure, which is independent of deregulation. Further, lower absenteeism and higher (unobserved) effort may be traced to rapidly growing earnings (**Chapter 6**). What is the evidence on the proposed causes of reductions in time lost? Average time lost in disputes fluctuated without a trend (Labour Bureau, several issues) but may well have declined in certain industry-state pairs. The incidence of machine failure probably fell with widespread technological upgrading, evidence of which is in Ahluwalia (1991, p.92). The 1980s did witness positive developments in infrastructural provisions (Section 2.1, **Chapter 5**). The absenteeism rate fell from 14.2% in 1977 to 12.7% in 1987 (Labour Bureau, several issues).

[39] Firm surveys conducted by the NCAER (1966) in a study of capacity utilization revealed that, in 1961-64, they assigned excess capacity to the following reasons, in descending order of importance: raw material difficulties, foreign exchange difficulties and labour troubles. 80% of the surveyed firms reported raw material difficulties. These were classified as arising from import restrictions, high cost, poor and variable quality, uncertain deliveries and high transport costs. As argued in Chapter 5, the causes of losses in *days* overlap with the causes of *excess capacity* in Indian industry.

This alone could account for almost all of the 1.6% p.a. rise in *days*[40].

To the degree that higher unobserved effort was the drag on employment in the 80s, its long run employment consequences are unclear unless further structure is imposed on the model (see *Efficiency* under **Section 3.2** above). However, to the extent that it is all about observed effort, this analysis offers the happy prospect that, given a natural ceiling to *days*, output growth will eventually re-establish employment growth[41]. Indeed, after bottoming out in 1986, employment growth in the period 1987-1989 has been positive. An independent reason for employment to pick up speed is if a given level of output generates more employment under more competitive conditions. There is evidence for India that industries with effective protection in excess of 70% in 1986 used more than five times as much fixed capital per employee as those with low protection (World Bank, 1987)[42].

One leg of our story rests on the idea that there was excess employment in the factory sector at the turn of the decade. This is consistent with rapid employment growth in the 1970s (**Table 5**) and with our finding of a negative effect of *days* on wages (per day worked), which implies the existence of *undertime*, a symptom of excess employment

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[40] The *level* of absenteeism is strikingly high. It may be accounted for by regular visits of factory workers to their villages (eg., National Commission on Labour, 1969) or by poor health, though we could not find concrete evidence of the latter.

[41] In **Chapter 5**, we estimate the following production function:

$$y = 0.7\ n + 0.3\ k + 0.9\ d + tfp$$

where d=days/worker and the other variables have the usual interpretations. Let the p.a. growth rate of X in the period 1979-87 be written as Δx. Then $\Delta y=6.3\%$, $\Delta n= -0.3\%$, $\Delta k=7\%$, $\Delta d=1.7\%$ (**Table 2**). The equation implies $\Delta tfp=2.8\%$. Note that the contribution of Δd to Δy is 1.6%, obtained as 0.9x1.7%. For purposes of a rough and ready calculation, assume that the structural parameters of production are unchanged and that the growth rates of other variables are maintained, but that days/worker hits a ceiling, so $\Delta d=0$. In such a case, employment growth must rise by 2.3% p.a. (i.e. 1.6/0.7) to compensate for Δd.

[42] It may be argued that, if seen as work-sharing, the slack is desirable as it will reduce unemployment. This view derives from 'the lump of output fallacy' which assumes that the amount of labour required is fixed and so sets scale effects to zero. An increase in days may well lead to a temporary decrease in employment. However this is expected to cause wage-pressure to fall and so to increase the total labour input (see Layard, Nickell and Jackman (1991), p. 73). In the medium term therefore, if other things are unchanged, employment should revert to its former level while the increase in working days is maintained.

(**Chapter 3**). Desai (1981a) records overmanning in public sector enterprises, which account for 30% of factory employment (ASI, 1987). The puzzle is then shifted to the question of why firms did not exploit this slack earlier, or of *why hoarding happened in the first place*. Surely, hoarded labour in a labour-surplus economy is somewhat paradoxical. In its full shape, this question is beyond the scope of the current study, and we know of no other attempt to consider it. Towards an explanation, the following arguments may be proposed.

(1) Firms were protected in their product markets. Therefore, the pressure to cut costs was not binding and they may not have been profit maximizing. There is evidence of substantial rents being earned in the factory sector (Bhagwati and Desai (1970), for example), and of these being shared with labour. Excess employment is a means of *rent-sharing*. This may have changed in the 1980s, as the rents began to be competed away on the product market.
(2) Firms were constrained by government objectives. Given this, hoarding may have been a rational response. Though more explicit for public enterprises, these constraints had some grip on private enterprises too. Workers have had the support of the government since Independence, expressed through pro-labour laws, affiliations of central trade unions with the major political parties, excessive employment in public enterprises and pressure on the private sector to generate jobs. There were also direct policy incentives. For example, firms with large capacities and large numbers of employees were favoured in the allocation of import licenses. The potential rents in this business were large enough to have encouraged both excess capacity and excess employment (eg.,Mohammed and Whalley, 1984). *This changed in the 1980s* with the phasing in of economic liberalization. The government began to woo managements and withdraw its support for workers (Davala, 1994). At the same time, the structures for protection of workers' interests became less effective as the structures for protection of firms' interests on the product market began to be dismantled.
(3) Workers were powerful in the 1970s. By the turn of the decade, their power is likely to have been *directly* undermined, *inter alia*, by the following sequence of events. The huge railway strike in 1974 was ruthlessly crushed. Mrs. Gandhi called a political emergency in 1975, and was voted out soon after. This resulted in a splintering of the impressive hierarchy of Congress (I) agents, which included some pivotal union leaders (see Devi

(1990), who incorporates the grassroots realities of these changes in a short story). The enormous textile strike (see Wersch 1988 and Bhattacharjee 1989), in the course of which many jobs (and lives) were lost, struck a further blow to extant union structures. More generally, the shrinking of regular jobs in the economy is expected to have reduced the bargaining strength of workers. When workers are less powerful, they are more likely to limit restrictive practices and accept management demands that they work harder, in terms of both time and effort. Evidence of declining union power was cited under **Section 6.2**.

(4) Many union leaders stemmed from political parties in the 1970s, and so it may have been in their interests to increase the numbers in their fold. With the new leaders coming from the work force in the 1980s (Ramaswamy, 1988), there was not only a diminishing of union power for want of high-level connections, but also a shift in worker priorities that appears to have made them more 'insider-oriented' and so, for example, more willing to trade wage increases for flexibility in job-description. For instance, Bhattacharjee (1987) estimates that independent, internal and employee-led unions negotiate 15% higher average pay than do the externally-affiliated unions.

(5) Changes in industrial composition in the 1980s, in favour of chemical-based process industries (Kelkar and Kumar, 1990) may have reinforced the tendency towards a relatively well-paid but small work force, to the extent that the technology in these industries favours a small, stable and hard-working group of workers[43].

(6) Energy prices were high in the 1970s. Since energy is required to operate capital, capital was implicitly more expensive than before. This may have led to some substitution of labour for capital. This was no doubt encouraged by the fact that consumer prices (and so, wages) were relatively tame in the 1970s (**Section 2.2**). Both tendencies were reversed in the 1980s.

A more convincing answer requires a deeper understanding of the political economy of the changes wrought in the 1980s, which is beyond the scope of the present study.

[43] Papola (1992, p.39) claims that technological changes in industry have contributed significantly to low employment growth, though he posits this as a continuing process through the 1970s and 80s and provides no evidence pertaining to the 80s.

In sum: There is likely to be at least a grain of truth in each of the proposed hypotheses. However, when considering the entire factory sector, the most plausible candidate would seem to be the last. To some extent this encompasses elements of the other explanations but at a secondary level. For example, the subcontracting out of production by large firms to small workshops and the increase in worker-days rather than workers may signify the bite of pro-labour laws and legislated fixed costs. However, if at all there was a change in this respect in the 1980s it was in the direction of looser enforcement of these laws, making it unlikely that they were a proximate cause of the stagnation in employment. It is important to emphasize that this section is woven on somewhat speculative threads. More information on the unregistered manufacturing sector and its relation to the registered sector, data disaggregated by public and private ownership of enterprises, and most of all, in-depth analyses of the experience of particular sectors would provide insights that we are lacking. We don't really know why *days* increased and it is difficult to establish increases in unobserved effort.

7. CONCLUSIONS AND REFLECTIONS

The analysis in this chapter characterizes the demand side of the Indian labour market. Special attention is paid to describing the role of imperfect competition in the specification of the theoretical model. Other somewhat novel features of the employment function estimated here are the treatment of technical progress, the use of region controls, and the analysis of employment dynamics.

The motivation of this work is to offer a perspective on the causes of the deceleration of manufacturing employment in the 1980s. The extent to which rising product wages can account for the decline in employment is taken up as the central issue. This is done partly to address a mistaken claim arising from an earlier study (World Bank, 1989), but also because academics and other observers have looked askance at improvements in the living standards of factory workers with the feeling that the relative standards of the organized working class have been growing out of proportion with the standards of the population at large (for eg., Dandekar 1987, Jose 1992). The analysis here establishes that it would be mistaken to attribute the poor employment record of the 1980s primarily to 'excessive' wage growth. To the extent that wage behaviour embodies the effects of union power and job protection, these institutional mechanisms are also pushed off-centre. Instead, it is argued that the outcomes observed in the registered sector labour market derive from changes outside it. These are, primarily, (a) improvements in public infrastructure and (b) deregulation and trade liberalization. The first enabled and the second induced efficiency, and the employment consequences were dramatic only because so much slack was inherited from the previous decade. A cheerful aspect of this analysis is that it implies that the fall-off in employment growth was an inherently short-term phenomenon[44]. Although this

[44] This is not to say that employment growth will remain unhampered in the face of *new events*. India took a huge IMF loan in 1991. Growth in manufacturing and GDP collapsed in 1991-92 and employment growth was dampened. There was some recovery in the following year but the growth rate remained below its former level. We need to wait for more data to appear. For now it is noted that this decline in employment growth *accompanied a decline in output growth*, and is believed to have been largely in public enterprises (informal sources).

hypothesis is not easily established, it appears consistent with the facts. To some extent, the decline in employment growth in the factory sector appears to have been the result of a shift in the size structure of manufacturing, accompanied by increased subcontracting on the one hand and increased casualization of the factory work force on the other. These structural changes may also be traced to the regime change that crept up on the 1980s.

Chapter 3 showed that rents were shared with workers by the payment of high wages. The analysis in this chapter suggests that, until the 1980s, rent-sharing may also have taken the form of labour hoarding. Labour hoarding would strike most economists as an unexpected outcome in a labour-surplus economy. Just like excess capacity would strike most economists as irrational in a capital-scarce economy. In fact, both can be understood as responses to policy interventions such as the conditions under which import licenses were granted (eg., Mohammed and Whalley, 1984). However excess employment can also be understood in terms of political constraints imposed on employers by a union-government nexus, along with the fact that small deviations from profit-maximization lead to only second order losses in profit for the agents concerned (Akerlof and Yellen, 1985).

Appendix 4.1

OUTPUT-CONSTRAINED EMPLOYMENT MODELS

Here, we specify the theoretical model estimated by the World Bank (1989) and other studies of Indian manufacturing employment. We have estimated such a model in **Section 5.2**. Profit maximization under imperfect competition gave us an employment function that is inherently a marginal revenue product condition (equation (6) in the text):

$$N = N1\ (K, A, W, \sigma^e) \tag{A.1}$$

where N=employment, K=capital, A=an efficiency index, W=product wage, σ^e=an indicator of expected demand. Exploiting duality, an alternative labour demand curve is derived by minimization of a cost function subject to a given technology (Varian 1984, p.54). This is

$$N = N2\ (Y, (W/C), A) \tag{A.2}$$

where Y=real value added output and C=user cost of capital. A third model (Rosen and Quandt (1978), for example) that is often estimated is obtained by substituting out K in (A.1), using the production function Y=Y(K,L,A). This gives:

$$N = N3\ (Y, (W/P), \sigma^e) \tag{A.3}$$

(A.3) is the equation estimated by the World Bank.

A comparison of the alternative employment models

Equations (A.2) and (A.3) are the most popularly estimated, estimation of (A.1) being relatively recent and confined to a few authors based in the U.K. (e.g. Nickell and Wadhwani (1991), Arellano and Bond (1991)). Andrews (1988) speculates that the relative neglect of (A.1) has probably arisen on account of the availability of quarterly data on output but not capital, and the difficulties of obtaining an accurate measure of capital stock. However, practical problems arise in estimation of the 'capital-free' models as well. In particular, output is highly endogenous in an employment equation, compared with capital which may be regarded as predetermined.

(A.1) is an unconditional labour demand schedule that corresponds most closely to the theoretical concept of a labour demand curve, insofar as one exists under imperfect competition. In comparison, (A.2) is a conditional demand curve, the employment decision being a question of finding the point on a *given* isoquant that minimizes costs given relative factor prices. This is only relevant when firms are output-constrained[1] or when the data pertains to an aggregate closed economy operating at full employment. Equation (A.3) bears the deficiency that it has a somewhat awkward status in theory. In particular it would not be correct to read the wage elasticity derived from estimation of this model as the slope of the labour demand curve[2]. It can be only be interpreted as a rearranged marginal productivity condition for a CES production function without CRS (Andrews, 1988). In this case, the wage coefficient is the elasticity of substitution.

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[1] The fact that less industrialized countries are often characterized as facing foreign exchange and capital constraints on growth may explain why this formulation has been favoured in the literature on developing countries. Of course, absence of reliable capital stock data stands as a further reason.

[2] The wage elasticity of employment in (A1) is $\sigma_{LK}/(1-\alpha)$, where σ is the elasticity of substitution between capital and labour. In (A3) it is σ_{LK} and in (A2) it is $\sigma_{LK}(1-\alpha)$, where α=the share of labour in (nominal) value added and σ_{LK}=the elasticity of factor substitution.

Appendix 4.2

RETURNS TO SCALE IN THE EMPLOYMENT FUNCTION: A PROOF

Here we demonstrate that a less than unit coefficient on capital stock in the employment equation implies decreasing returns to scale. Consider a general production function:

$$VA = F(N,K), \tag{1}$$

where VA=value added, N=employment, K=capital stock. Profit maximization gives the marginal revenue product condition:

$$F_N\ (N,K) = W/P, \tag{2}$$

where F_N is the partial derivative w.r.t. N, W/P=the product wage.
It follows that if (1) is homogeneous of degree α then (2) is homogeneous of degree $(\alpha\text{-}1)$. Thus if (2) is to be written as a function of (N/K), we have:

$$K^{\alpha-1}\ F_N\ ([N/K],\ 1) = W/P \tag{3}$$

If the technology is characterized by constant returns to scale then, by definition, α=1. Thus (3) reduces to

$$F_N\ ([N/K],\ 1) = W/P \tag{4}$$

which implies that if N were regressed on W/P and K we would obtain a long run coefficient on K of unity. However if α is not equal to 1 then (3) may be rewritten, in logarithms, as:

$$\log N = \log K + \log F_N^{-1}\ ([W/P]\ K^{1-\alpha}) \tag{5}$$

Differentiating to obtain an expression for the coefficient on K gives:

$$\mathrm{dlog}N/\mathrm{dlog}K = 1 + \{\mathrm{dlog}F_N^{-1}()/\mathrm{dlog}()\}.\{\mathrm{dlog}()/\mathrm{dlog}K\} \tag{6}$$

By the law of diminishing marginal productivity F_N, and therefore F_N^{-1}, is decreasing in K and the first part of the second term is negative. From (5) it is clear that the second part of the second term, dlog()/dlogK=(1-α). Thus:

$$\text{dlogN/dlogK} = 1 + (\alpha-1) \tag{7}$$

which proves that if the coefficient on log K in a (logarithmic) employment equation is less than 1 then α<1 or there are decreasing returns to scale. Since we will be working with a Cobb-Douglas production function this principle is now illustrated for the special case: F(N,K) = A N^a K^b, which is a general Cobb-Douglas production function for which returns to scale, α=(a+b). The marginal product condition is:

$$W/P = F_N(N,K) = a\ A\ N^{a-1}\ K^b, \text{ or } N^{a-1} = [1/aA]\ [W/P]\ K^{-b} \tag{8}$$

which in log-linear form is

$$n = \gamma + (1/[a-1])\ [w-p] - (b/[a-1])\ k \tag{9}$$

where γ=(-log a- log A)/(a-1). It is evident that if there are constant returns to scale or (a+b) = 1 then b = [1-a] and the coefficient on capital will be +1. If there are decreasing returns to scale or (a+b) < 1 then b < (1-a), implying that the capital coefficient will be positive and less than 1. By symmetry, if there are increasing returns to scale (IRS) then the coefficient on capital will be positive and greater than 1. The *intuition* of this result is as follows: The coefficient on K in the employment equation is estimated under the condition that the product wage or equivalently, the marginal product of labour, is held constant. If the technology shows constant returns then it is simple to demonstrate that F_N (K,N) = F_N (λK,λN) or that the marginal product of labour is invariant to an equal proportional change in both factors. The fact that F_N is an increasing function of K and a decreasing function of N is consistent with the general idea that both factors must increase in order that F_N is unchanged. In the case of DRS, in order that F_N be constant, N must increase less than proportionally to K. This will be reflected in a capital coefficient of less than 1 in an employment equation.

Appendix 4.3

THE STANDARD ERROR OF ESTIMATE OF A NON-LINEAR PARAMETER

Long-run elasticities

Let $n = \alpha 1\ n_{-1} + \alpha 2\ n_{-2} + \beta 1\ x_{-1} + \beta 2\ x_{-2}$. Then the long run elasticity of n with respect to x is $\xi = [\beta 1 + \beta 2] / [1 - \alpha 1 - \alpha 2]$, which is a non-linear function. The problem is to estimate a standard error of estimate of ξ given the estimated standard errors on the α's and β's. Begin by letting θ be a (4 x 1) vector of the model parameters and V be the associated (4 x 4) variance-covariance matrix. We may then write $\xi = f(\theta)$ and $var(\xi) = [\partial f/\partial\theta]\ V\ [\partial f/\partial\theta]'$, where $[\partial f/\partial\theta]$ is a (1 x 4) vector of partial derivatives of the elasticity w.r.t. its arguments and $[\partial f/\partial\theta]'$ is its transpose, a (4 x 1) vector. We know that $x'Ax = \sum_{i,j} a_{ij}\ x_i\ x_j$, and if A is a diagonal matrix then $a_{ij}=0$ for $i \neq j$, and $x'Ax = \sum_i a_{ii}\ x_i^2$. Since $cov(\alpha_i, \alpha_j)=0$ if $i \neq j$ and $cov(\alpha_i, \beta_j)=0$ for all i,j, V is a diagonal matrix, the stated simplification can be used to compute the variance as:

$$\sigma^2(\xi) = \sigma^2(\alpha 1)\ ([\beta 1+\beta 2]/[1-\alpha 1-\alpha 2]^2)^2 + \sigma^2(\alpha 2)\ ([\beta 1+\beta 2]/[1-\alpha 1-\alpha 2]^2)^2$$
$$+ \sigma^2(\beta 1)\ (1/[1-\alpha 1-\alpha 2]^2) + \sigma^2(\beta 2)\ (1/[1-\alpha 1-\alpha 2]^2),$$

$$= (\sigma^2(\alpha 1) + \sigma^2(\alpha 2))\ ([\beta 1+\beta 2]/[1-\alpha 1-\alpha 2]^2)^2 + (\sigma^2(\beta 1) + \sigma^2(\beta 2))\ (1/[1-\alpha 1-\alpha 2]^2)$$

the square root of which is the standard error of estimate of the long run elasticity of x.

The speed of adjustment in a second-order employment equation

The estimated employment equation can be written as a quadratic polynomial in the lag operator (L) : $(1 - \lambda_1 L - \lambda_2 L^2)n = x\beta + \varepsilon$. In general, the roots of a quadratic polynomial of the form $ax^2 + bx + c = 0$ are given by:

$$\{\ [-b \pm (b^2-4ac)^{1/2}] / 2a\ \},$$

which is a non-linear function of a,b and c. In our equation, $a=1$, $b=-\lambda_1$ and $c=-\lambda_2$. Thus the standard error of estimate (σ) of the dominant root (R1), when it is real, can be shown to be given by:

$$\sigma^2(R1) = \sigma^2(\lambda_1)\ [R1^2/(\lambda_1^2 + 4\lambda_2)] + \sigma^2(\lambda_2)\ [1/(\lambda_1^2 + 4\lambda_2)]$$

CHAPTER 5
THE PRODUCTION TECHNOLOGY AND PRODUCTIVITY

INTRODUCTION

Chapter 4 was devoted to explaining the fact that there was no growth in factory employment during 1979-87, a period when value added in Indian factories soared. It follows that there was rapid growth in labour productivity. Arguably more interesting is the fact that capital productivity also improved relative to recent history. As a result, there was a significant increase in total factory productivity growth (TFPG) in the 1980s. This is of immense significance in India. One reason is that the imperative to make the most of its resources is stronger in a low income country. Furthermore, a process of industrial deregulation was begun in the 1980s and developments in this decade are a comment on the policy shift. So far, there is one study of TFPG in the 1980s (Ahluwalia, 1991) and it has generated a great deal of interest. Our contribution consists primarily in improvements in methodology, although we also offer a somewhat different perspective on the forces underpinning the acceleration in productivity.

The analysis is conducted for aggregate manufacturing as well as for its two-digit industries. In **Part 1**, we estimate production functions which provide us with estimates of returns to scale, time-invariant efficiency effects and the productivity contribution of growth in days worked per worker. **Part 2** concentrates on productivity measurement. Growth rates of TFP are obtained from the production function estimates, using a *modified* Solow algebra. They are rather different from the estimates obtained by use of the *traditional* Solow algebra, under the assumption of perfect competition.

PART 1: PRODUCTION FUNCTIONS

In this section, we estimate production functions, which yield measures of three dimensions of efficiency: scale, allocative and technical. The labour input is specified so as to separate employment and the number of days worked and the place of the days variable in the production function is investigated. This exercise faces the well-established problems of aggregation, identification and errors of measurement. Within the constraints imposed by the available data, these are addressed. After a brief summary of similar work for Indian manufacturing (**Section 1.1**), we set out the basic specification and identify the parameters of interest. We also consider alternative functional forms and a role for dynamics (**Section 1.2**). In **Section 1.3**, we discuss estimation issues and so proceed to develop the econometric model. Finally, we discuss the estimated parameters, first for the entire manufacturing sector (**Sections 1.4, 1.5**) and then for its constituent industries (**Section 1.6**).

1.1. EXISTING WORK

Thus far, the thesis has covered relatively unexplored territory. This is not the case for this

Table 1.1
Some Existing Estimates of the Cobb-Douglas Function for Indian Manufacturing
Dependent variable=ln(y-n)

Author/Period	Data	Domain	Estimator	(k-n)	n	trend	strend*	Goodness
Murti & Sastry 1950	CS N=320	firm survey	OLS	0.50				
Goldar 1951-65	TS T=15	census sector	OLS	0.22 (1.4)	0.31 (0.7)	0.024 (2.1)		R^2=0.95 DW=1.7
Goldar 1959-78	TS T=19	census sector	OLS	0.29 (2.2)	0.30 (0.9)	0.007 (0.7)		R^2=0.95
Ahluwalia 1959-85	TS T=27	factory sector	OLS	0.31 (1.6)	-0.45 (1.1)	0.018 (0.9)	0.004 (2.0)	R^2=0.95 DW=1.7
Ahluwalia 1959-85	Panel NT=2240	factory sector	WG	0.50 (23.4)	0.07 (4.1)	-0.007 (4.2)	0.007 (8.6)	R^2=0.87

Notes: The t-statistic associated with n affords a test of the constant returns to scale hypothesis. (*):*strend*=a split trend defined as 1982-85=1, else 0. TS=time series, CS=cross-section, N=CS observations, T=TS observations, DW= Durbin -Watson statistic. See **Data Appendix** for definitions of sectors/estimators. *Sources:* Murti and Sastry (1957), Goldar (1983), Ahluwalia (1991, p. 153, row 3 and p. 178 col 4).

chapter. Estimates of the production function parameters in Indian manufacturing have been around for a long time. An instance of an early contribution is that of Murti and Sastry (1957). By now, there is a thick accumulation of studies. The findings of some of the more reliable ones are gathered in **Table 1.1**; Goldar (1983) provides a more comprehensive survey of the literature. Most of the available studies use aggregate time series data and, it appears, not one takes account of endogeneity of the regressors. Further, *all* existing studies measure the labour input as employment, neglecting to control for variations in hours (or *days*). Although the productivity turnaround in the early 1980s is now a well-established fact, the role of increasing days worked per worker has not been recognized.

1.2. THE MODEL

1.2.1. The Cobb-Douglas Production Function

Suppose that the production of value added in real terms (Y) can be described by the function (Cobb and Douglas, 1928),

$Y_{jt} = a_{jt}\, N^{\beta n}{}_{jt}\, K^{\beta k}{}_{jt}$, which in natural logarithms is

$$y_{jt} = \beta_n n_{jt} + \beta_k k_{jt} + \nu_{jt} \tag{2a}$$

Lowercase letters denote logarithms, j=firm subscript, t=time subscript, y=real value added, n=employment, k=capital stock and ν=ln a, is a disturbance term. The β's are the elasticities of output with respect to labour and capital respectively and $(\beta_n+\beta_k)$ is an estimate of returns to scale (RTS).

The level and growth of productivity

The disturbance term ν in the production function is commonly known as total factor productivity (TFP). This can be written in terms of its components as

$$\nu_{jt} = \mu_j + \tau_t + \varepsilon_{jt} \tag{2b}$$

Here μ_j is a firm-specific effect that reflects heterogeneous technologies, management skills, ownership, location, the vintage of capital stock, and other time-invariant factors that impact on efficiency *levels*. The second component, τ_t, is a productivity *growth* effect common to all firms. It will include, for example, technological progress, changes in capacity utilization and any common productivity consequences of changes in industrial regulation. Residual noise reflecting technical efficiency and measurement errors in y is picked up by ε_{jt}, which is assumed to be identically and independently distributed across firms and time, and uncorrelated with the exogenous variables.

Days worked per worker

As a measure of labour utilization, we use *actual* days worked per worker ($days_{jt}$) which is precisely the contribution, in terms of time, of a worker to the production process. Existing studies for Indian manufacturing neglect variations in work intensity. In the broader literature, the labour input is often specified as total 'manhours' (eg., Solow, 1957). This is equivalent to assuming that increases in *days* (hours) are labour-augmenting or that days worked and workers are perfect substitutes. However, it has been observed that the marginal productivity of average hours worked tends to exceed that of employment (eg., Feldstein (1967), based on British cross-sectional evidence and Craine (1973), based on US time-series). One reason is that workers incur start-up costs (eg., 'warming up', tea breaks) that get spread more thinly with additional hours. Some frictional loss may arise from new workers having to be socially accepted by existing workers. Furthermore, an additional day worked not only employs more worker time but also results in higher capital utilization. The unit cost of capital services falls since the sum of depreciation and interest rises less than proportionately with hours of use of the capital stock. So if the production function with *days* (*D*) incorporated is

$$Y_{jt} = e^{v}_{jt}\, D^{\beta d}_{jt}\, N^{\beta n}_{jt}\, K^{\beta k}_{jt}, \tag{4}$$

then we expect that $\beta_d > \beta_n$, although we investigate the labour-augmenting restriction ($\beta_d = \beta_n$). A quadratic term in days is also included to allow for convexity or decreasing returns as a second order effect.

Skill composition

Another productivity factor that shows firm and time variation is skill. In the absence of a direct measure, we use the ratio of all employees to production workers ($skill_{jt}$). It is expected that non-production workers are the more skilled, although a positive impact of this variable on output could equally arise from the notion that output per production worker is higher when there are more supervisory staff in the enterprise.

1.2.2. Generalizing The Simple Model

Alternative functional forms

We have specified a simple Cobb-Douglas technology on the grounds that it provides a reasonable local approximation to any more complex technology that may prevail. Moreover, its simplicity affords flexibility in dealing with the econometric problems that beset production function estimates. As early as 1948, Douglas reported that it provided a good fit to data pertaining to a large number of countries and industries, and since then, evidence in its favour has been accumulating. Other researchers have reported that the available data often do not support sophisticated functional forms (see, eg., Griliches and Ringstad, 1971). Nevertheless, in order to investigate the restrictiveness of the Cobb-Douglas function, we estimate the alternative form specified in (7) below.

The translog function under CRS

The translog function (Christensen, Jorgensen and Lau, 1973 and Berndt and Christensen, 1973a) can be written as:

$$y = \beta_n n + \beta_k k + (1/2)\beta_{nn}\, n^2 + (1/2)\beta_{kk}\, k^2 + \beta_{kn}\, kn + \nu \qquad (5)$$

The variables are defined as in (1) and we have dropped subscripts, *days* and *skill* so as to avoid clutter. It is evident that (5) encompasses (2). To investigate the treatment of returns to scale, allow both N and K to increase by the proportion e^{λ}. Then,

$$y = \beta_n\, (n+\lambda) + \beta_k\, (k+\lambda) + (1/2)\beta_{nn}\, \{n^2 + 2n\lambda + \lambda^2\} + (1/2)\beta_{kk}\, \{k^2 + 2k\lambda + \lambda^2\}$$

$+ \beta_{kn} \{kn + n\lambda + k\lambda + \lambda^2\} + \nu$ (6)

Let us now impose constant returns to scale (CRS). This requires $\beta_n + \beta_k = 1$ and $\beta_{nn} = -\beta_{kn} = \beta_{kk}$. Imposing these equalities reduces the ten second-order terms to $-\beta_{kn}(k-n)^2$. Homogeneity of degree one in this quadratic expression is transparent. Thus under CRS,

$$(y-n) = \beta_k(k-n) - \beta_{kn}(k-n)^2 + \nu \tag{7}$$

which is a far simpler form than (5).

A linear approximation of the CES function

The constant elasticity of substitution (CES) form is

$$Y = a\ [\beta_n N^{-\rho} + \beta_k K^{-\rho}]^{-\theta/\rho} \tag{8}$$

As in equation (2), e^{ν} incorporates the level and growth of TFP, θ is the scale parameter and ρ, the substitution parameter, the Cobb-Douglas function being a special case corresponding to $\rho=0$ (Arrow *et al*, 1961). The elasticity of factor substitution is $\sigma=1/(1+\rho)$, where $0<\sigma<1$. Expanding (8) in a Taylor series around $\rho=0$ gives the first-order log-linear approximation

$$y = \beta_n n + \beta_k k - (1/2)\beta_n\beta_k\rho(1/\theta)(n-k)^2 + \nu \tag{9}$$

where $\nu=\ln a$. Assuming $(\beta_n+\beta_k)=1$ or CRS, (9) reduces to

$$(y-n) = \beta_k(k-n) + \beta_{kn}(k-n)^2 + \nu \tag{10}$$

which is equivalent to (7). This is the equation that we estimate once we have evidence of CRS in our data. It is less restrictive than the Cobb-Douglas equation and simpler than the unrestricted CES and translog functions.

Adjustment Lags

The production functions discussed thus far are static. In fact there may be some lag in the appearance of increased output on account of lags in the adjustment of new inputs to the production environs, in which case the long run impact of an input on output will exceed its short run impact. For example, the training of new hires takes time. To allow for this, we introduce the lagged dependent variable into the production function.

1.3. ESTIMATION ISSUES AND THE ECONOMETRIC SPECIFICATION

1.3.1. Estimation Issues

Keeping to the static Cobb-Douglas form for the moment, the equation to be estimated can be written log-linearly as

$$y_{jt} = \beta_n n_{jt} + \beta_k k_{jt} + \beta_d days_{jt} + \beta_{dd} days^2_{jt} + \beta_s skill_{jt} + \mu_j + \tau_t + \varepsilon_{jt} \tag{11}$$

The following estimation issues arise. If any of the right hand side variables is (positively) correlated with the unobserved fixed effects, μ_j, then the OLS estimate of this variable will be biased (upward). This is the *heterogeneity* problem. A second potential problem is *endogeneity*, or a correlation between any of the explanatory variables and the random component of the error, ε_{jt}. A third issue is that of possible *measurement error biases.* There is also the question of whether the *common slope restrictions* in (11) are valid. Finally, the distribution of shocks to different firms (or, states and industries) will, in general, not be identical. So the disturbance term will be *heteroskedastic* when the equation is estimated on a panel, and the chosen estimator should take account of this.

Heterogeneity of the intercepts

It seems reasonable to assume that managers have some knowledge of the firm's slowly changing productivity determinants, such as the vintage of its capital stock. Assuming that they choose the levels of the inputs in view of expected profitability, the inputs will be correlated with μ_j (Zellner *et al,* 1966). Alternatively, if relatively capital intensive firms have better managers, then the correlation of the residual with capital will be positive and, with employment, negative. A further reason why the fixed component of the error may be correlated with the inputs is provided by Demsetz (1973), who predicates a positive correlation between factor demands and productivity levels on the notion that large firms grow large because they are relatively efficient[1]. The resulting heterogeneity bias is easily eliminated by transforming the equation so as to eliminate the μ_j. The standard method is the within-groups transformation, although differencing the equation is just as effective. The choice between these transformations is guided by the other estimation issues.

Endogeneity

Suppose that the fixed effects have been eliminated. Employment may still be endogenous to output for given capital stocks if the aforementioned effects operate through ε_{jt} rather than μ_j or if output shocks impact on employment. For the same reason, *days* is also potentially correlated with the innovations, ε_{jt}, and in fact the correlation is more likely because the costs of adjusting days are smaller than those of adjusting employment (**Chapter 4**, Section 5.1). Whether because of heterogeneity or endogeneity, if the error is correlated with the inputs then the OLS returns to scale (RTS) parameter $(\beta_n+\beta_k)$ incorporates the following bias (see, for example, Tybout and Westbrook, 1991) :

$$\text{bias }(RTS)_{OLS} = [\text{cov}(\nu_{ist}, k_{ist}) + \text{cov}(\nu_{ist}, n_{ist})] \,/\, (r + 1) \qquad (12)$$

where $\nu_{ist} = \mu_j + \tau_t + \varepsilon_{jt}$, r=corr(k,n) and by normalization, var(k)=var(n)=1. Dealing with the endogeneity bias requires instruments. Valid instruments are uncorrelated with the error while being highly correlated with the endogenous variable. Under within groups (**WG**), the transformed error involves shocks of every time period in the sample but, under the first difference (**FD**) transformation, the error involves only the current and the last period. For this reason, it is easier to find valid instruments for the FD model and, by this criterion, it is preferred over WG.

Measurement error

The choice between alternative estimators is not clear-cut if, in addition to heterogeneous

[1] Related arguments linking productivity and factor demands have appeared several times since Marschak and Andrews (1944). For instance, Jovanovic (1982) has formalized the Demsetz argument in a dynamic learning model in which firms discover their efficiencies through market experience and eventually expand or exit.

efficiency levels and endogenous regressors, there are errors in variables. Let us consider an example. Published data report the book value of capital, K, which is an accounting measure based on historic purchase costs and smooth depreciation rates. Inflation and book-keeping conventions create substantial discrepencies between this and the true (unobservable) value of capital stock[2], K^*. Using the perpetual inventory method, we adjust the book value to get estimates of gross stock at replacement prices (**Data Appendix**). However, this entails various approximations and so is likely to contain some measurement error (u). Hence, in logs,

$$k_{jt} = k^*_{jt} + u_{jt} \tag{13}$$

The error u is assumed homoskedastic with variance σ^2_u, and uncorrelated with v, k and n (refer eq.2). The production function in levels is

$$y_{jt} = \beta_n n_{jt} + \beta_k k_{jt} + \beta_d days_{jt} + \beta_{dd} days^2_{jt} + \beta_s skill_{jt} + [\mu_j + \tau_t + \varepsilon_{jt} - \beta_k u_{jt}] \tag{14}$$

The appearance of the measurement error ($-\beta_k u$) in the composite disturbance term biases the estimated capital coefficient towards zero. The OLS bias is (eg., Kmenta, 1986):

$$\text{bias } \beta_{k(OLS)} = -\ \beta_k \sigma_u^2/\text{var}(k) \tag{15a}$$

The within (WG) and difference (FD) transformations only tend to exacerbate this bias, with FD typically having a larger bias than WG. Griliches and Hausman (1986) show that, under these transformations, the measurement error (*or ME*) biases [$\text{plim}_{n\to\infty}(\beta_k - \beta_k^{true})$] on the capital coefficient is

$$\text{bias } \beta_{k(WG)} = -(T-1)/T\ [\beta_k \sigma_u^2/\text{var}(k_{WG})] \tag{15b}$$

$$\text{bias } \beta_{k(FD)} = -2\ [\beta_k \sigma_u^2/(\text{var}(\Delta k)] \tag{15c}$$

where $k_{WG} = k_{jt} - [(1/T)\Sigma_t(k_{jt})]$. In each case, the absolute magnitude of the bias depends on the

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[2] Indian firms may have an incentive to report exaggerated estimates of invested capital in situations where this puts them in a favourable position to compete for licenses. These deficiencies in the data reduce the power of standard estimators.

noise to signal ratio. Equations (15) establish that bias $\beta_{k(FD)}$ > bias $\beta_{k(WG)}$ > bias $\beta_{k(OLS)}$, since var(k) > var (k_{WG}) > (1/2)var(Δk)[3]. This ordering of the biases is confirmed for our sample, where var(k)=13.44, var (k_{WG})=0.201 and (1/2)var(Δk)=0.115. Now, as long as the coefficient on capital is biased by virtue of its correlation with the compound error, the labour coefficient is biased by virtue of its correlation with capital. If r is the correlation coefficient between the transformed k and n, then the induced bias in the estimate of β_n [$\text{plim}_{n\to\infty}(\beta_n-\beta_n^{true})$] is given by Westbrook and Tybout (1993, Appendix 1) as

$$\text{bias } \beta_n = -r[\text{bias } \beta_k] \tag{16}$$

So ME biases β_n upwards and β_k downwards and since r<1, the returns to scale parameter, $\beta_n+\beta_k$, is biased downwards.

With both the WG and FD estimates at hand, a consistent estimate of the true parameter and of the measurement error variance can be retrieved as:

$$\beta_k^{true} = [2\beta_{k(WG)}/\text{var}(\Delta k)-(T-1)\beta_{k(FD)}/(T\ \text{var}(k_{WG}))] \ / \ [2/\text{var}(\Delta k)-(T-1)/(T\ \text{var}(k_{WG}))] \tag{17a}$$

$$\sigma^2_u = (\beta_k^{true} - \beta_{k(FD)})\text{var}(\Delta k)/2\beta \tag{17b}$$

Having obtained 'β_k^{true}', we can use (15) and (16) to obtain 'β_n^{true}'. However, if the WG and FD estimates are corrupted by a combination of *endogeneity and* ME biases, this approach will not recover the true coefficients. Therefore, we look to an instrumental variables (IV) estimator that will take care of endogeneity and ME at once. Even though first differencing induces a larger ME bias than the within transformation, it may be preferred because it makes it easier to find valid internal instruments (see discussion of endogeneity above). Consistent estimates can be obtained by using a generalized method of moments (GMM) estimator (refer Section 3.2.2, **Chapter 3**). Not only are the GMM estimates asymptotically free of measurement error, but they also control for *heteroskedasticity*. Under the assumption

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[3] The variance of the levels variable is the sum of the within and between variances and so will always exceed the within variance. It can be shown that var(Δk) = 2(1-ρ)var(k_{WG}) where ρ=corr(k,k_{-1}). So (1/2)var(Δk)<var(k_{WG}) since, typically, ρ>0.

that the error process is serially uncorrelated in levels, values of the mismeasured variable(s) dated (t-2) and beyond are valid instruments for the first differenced variables. However, this assumption is not valid if the error originates in investment and K is constructed by the perpetual inventory method (or PIM)[4]. Let $i_t = i_t^* + w_t$, where i=investment, *=true value, w=measurement error. If δ is the rate of depreciation, then by the PIM,

$$k_t = (1-\delta)k_{t-1} + i_t = (1-\delta)k_{t-1} + i_t^* + w_t \tag{18}$$

Since true capital stock $k_t^* = (1-\delta)k_{t-1}^* + i_t^*$, the error in k is $k_t - k_t^* = (1-\delta)(k_{t-1} - k_{t-1}^*) + w_t$. Denoting the error by u, $u_t = (1-\delta)u_{t-1} + w_t$, which is an AR(1) process. If error does in fact arise in measuring investment, then the ME bias cannot be eliminated merely by using lags of capital as instruments. Therefore we must seek alternative instruments for the capital stock. Lags of output, employment and days worked are evident candidates. Since factor demands are co-determined with the technological relationship described by the production function, lags of the real wage may be effective instruments.

Although employment and *days* are less commonly associated with ME, we think it unlikely that factors like response variations and data processing errors are entirely negligible in the ASI statistics. Thus, in principle, we regard all variables used in the analysis as possibly marred by measurement inaccuracies of a random nature. In practise, employment and days are instrumented on account of potential endogeneity, and potential measurement error only enhances the motivation for doing this.

1.3.2. The Econometric Model

Data and variables

The data and variables are described in the **Data Appendix**. They are a panel of 18 industries spread across 15 Indian states, covering the period 1979-87. There are potential aggregation problems with the estimation of production functions on sectoral data. For

[4] This idea is introduced by Griliches and Hausman (1986).

instance, biases may arise from unstable coefficients attributable to compositional changes within industry groups. On the other hand, survey data, at least from poorer countries, tend to have measurement errors, missing observations and selectivity biases (Tybout, 1992). Further, because our panel covers all plants with ten or more workers with power and twenty or more without, it provides a much broader base for generalization than do detailed studies of specific firms or industries.

Value added data are available in nominal terms and are deflated by the wholesale price index for industry output (P_{it}). This will introduce some error if, for instance, the composite material price has experienced a good deal of *industry-time* variation. Moreover, P_{it} is subject to the three biases identified by Muellbauer (1984), the domestic-price, list-price and price-control biases. No attempt is made to 'undo' these biases and it is difficult to assess their quantitative significance. Employment is the number of employees, including production and non-production workers in an average ratio of 2:1. This ratio is used as a proxy for skill. The ratio of *mandays* to all employees (or *days*) measures labour utilization. The measure of capital is gross stock at replacement costs.

The econometric specification

Subscript *'j'*, so far employed to refer to the firm, is replaced with *'is'*, denoting industry-state. Heterogeneity bias is eliminated by first differencing the model and endogeneity and measurement error problems are tackled by instrumenting the endogenous and mismeasured variables. The GMM estimator used takes advantage of the existence of alternative consistent estimators, that is, of over-identification (see Section 3.2.2, **Chapter 3**). Reported standard errors are heteroskedasticity-consistent. The estimated equation is

$$\Delta y_{ist} = \beta_n \Delta n_{ist} + \beta_k \Delta k_{ist} + \beta_d \Delta days_{ist} + \beta_{dd} \Delta days^2_{ist} + \beta_s \Delta skill_{ist} + \theta_t + \Delta e_{ist} \tag{19}$$

where $\Delta e = \Delta v - \beta_k \Delta u$ has been purged of μ_{ist} and θ_t is obtained by differencing τ_t. These are year dummies that sweep out the common time effects in the data, including common changes in capacity utilization. We have mentioned the possibility that neglecting to control for fixed efficiency effects (μ_{is}) will result in inconsistent estimates. In fact, even the time effects may be correlated with the explanatory variables, making it important to control for them. We estimate (19) by GMM but also report the results of using more naive estimators. Comparing the alternative estimates is expected to provide some insight into the practical importance of the different econometric problems discussed in this section. In **Section 1.6**, we relax the *common slopes restriction* in (19) and estimate industry-specific production functions.

1.4. RESULTS: THE AGGREGATE PRODUCTION FUNCTION

Alternative estimation methods

Table 1.2 reports alternative estimators of the simple static Cobb-Douglas specification in (19). In all cases, time dummies (θ_t) are included and are significant. As *days*^{2} is not significant, whatever the estimator, it is not reported. Likewise, *skill* is also not retained. It is positive but insignificant in all but the levels-OLS model, which suggests that it may be well proxied by the industry-state fixed effects. The **levels-OLS** model in column (1) produces a very large coefficient on employment (β_n) and an implausibly small coefficient on capital stock (β_k). The unit coefficient on *days* (β_d) looks reasonable but will incorporate an upward bias if *days*, like employment, is positively correlated with the fixed effects. In column (2) is an OLS model that allows for industry *and* state effects, though not for industry-state effects. In this sense it is a halfway house between the OLS model in (1) and the WG model in (3). The fact that columns 2 and 3 are significantly different makes the point that the *industry-state interaction* is significant in determining efficiency levels. So, for example, different regions are more or less hospitable to different industries.

Comparison of columns 1 and 3 brings out the role of *heterogeneity biases*. The WG estimate of β_n is considerably smaller than the corresponding OLS-levels estimate, establishing that the latter carries a positive heterogeneity bias. The same is true of β_d, suggesting that *relatively efficient enterprises work more days in the year*. The WG estimate of β_k is much larger than the corresponding levels estimate, and it is now significant. Thus it appears that invariant levels of efficiency are negatively correlated with the capital stock, which may be a sign of *overcapitalization* induced by the *licensing raj*. Column 4 reports the OLS estimates of a first-differenced (**FD-OLS**) model. These are not significantly different from the WG estimates.

Table 1.2
Production Function Estimates
ALTERNATIVE ESTIMATION METHODS

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator/ Regressor	***Levels-OLS***	***Levels-OLS+γ_i+γ_s***	***WG***	***FD-OLS***	***GMM: internal IV***	***GMM: add external IV***
employment	0.99 (24.8)	0.64 (15.4)	0.62 (8.9)	0.69 (5.72)	0.70 (3.4)	0.69 (3.4)
capital stock	0.065 (6.5)	0.41 (12.1)	0.22 (5.5)	0.20 (3.5)	0.26 (1.7)	0.33 (2.5)
RTS	1.06 (25.8)	1.05 (19.6)	0.84 (10.5)	0.89 (6.7)	0.96 (3.7)	1.02 (4.25)
days/worker	1.09 (5.5)	0.54 (3.8)	0.45 (3.8)	0.47 (3.5)	0.55 (1.1)	0.93 (2.4)
Wald (γ_t)	42.2/6 (0.00)	14.2/6 (0.03)	66/7 (0.00)	63.3/7 (0.00)	18.9/7 (0.01)	17.6/7 (0.0)
R^2	0.86	0.94				
σ^2	0.41	0.196	0.13	0.115	0.115	0.12
ser corr(2)					0.29 (0.77)	0.70 (0.48)
Sargan					52.9/42 (0.12)	56.5/57 (0.49)

Notes: *Number of observations* (NT)=2080, T_{max}=8. *Dependent variable*=log real value added (y). The *s.e. on the RTS* (returns to scale=$\alpha+\beta$) parameter is derived as the square root of ($\sigma^2_\alpha + \sigma^2_\beta$). *Instruments* are [e,k,d](2,4),γ_t in col. 6 and the same plus w(2,4) in col. 7. See **Data Appendix 2** on notation.

Although WG and OLS-FD can be guaranteed to eliminate heterogeneity biases, they leave the estimates possibly marked by a *simultaneous equations bias*. Moreover, any *measurement error bias* is exacerbated. Both of these problems may be ameliorated with appropriate instruments. In column 5, we report **GMM** estimates of the production function that use **internal instruments**. Employment and *days* are instrumented for the reason that they are potentially endogenous and capital is instrumented because it is measured with error. The instruments are validated by the serial correlation and Sargan tests. Under IV, the output elasticity of capital rises, which is consistent with error in the capital measure, and the returns to scale parameter comes to approximate unity. However, the parameter estimates in col. 5 are not significantly different from those in col.4. Either the ME and endogeneity biases are not large or our instruments are weak[5]. Also, the estimates in col. 5 are not very well determined, especially β_d. Hence we incorporate lagged values of the product wage as **external instruments** in column (6). The wage is expected to be correlated with the capital stock by virtue of its correlation with profitability, and with employment (and *days*) by virtue of being the price of labour. Its second and further lags are expected to be uncorrelated with the differenced disturbance term.

The new estimates are better determined and the Sargan difference statistic is 8.4 (χ^2_{15}=25), which implies that the additional moment restrictions cannot be rejected. Therefore, the estimates in column (6) are preferred. Comparison of col.6 with 4 shows a rise in β_k, which suggests the existence of ME (or endogeneity) and some success in correcting the consequent bias. The GMM employment elasticity is much the same as the corresponding FD-OLS estimate[6]. There is a dramatic rise in the *days* coefficient, though its standard error is large enough that it is not significantly different from the earlier estimates[7]. In view of this ambiguity, we proceed to investigate restrictions on β_d.

The place of days worked per worker

Refer to **Table 1.3**. Column 1 reports the unrestricted model in column 6 of **Table 1.2.** Since the unrestricted point estimate on *days* is close to one, in column 2 we impose the restriction that β_d=1 by specifying the dependent variable as *output per day (y-d)*. The Wald

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[5] In **Section 1.3.1** we have shown that if the ME is in investment, then lags of the capital stock are not useful instruments. Since there is no indication of second order serial correlation in the residual of the estimated models, it now seems unlikely that our measure of capital incorporates an AR(1) error. Nevertheless, additional instruments may help.

[6] It is possible that the correction for induced ME bias (eq.16) offsets the correction for endogeneity bias in β_n.

[7] Using British inter-industry data to obtain the first unrestricted estimate of the marginal product of days, Feldstein (1967) also found a very high standard error on hours. He explains this as reflecting the fact that hours vary less across industries than do employment and capital.

test of the restriction is 0.18, indicating confidence in the restriction at the 95% level[8]. In column 3, we impose the labour-augmenting restriction, namely, $\beta_d=\beta_n$ by defining the labour input as total *mandays* worked (*m*). Again, *days* is included as an additional variable

Table 1.3
Production Function Estimates: GMM
THE PLACE OF DAYS IN THE MODEL

	(1)	(2)	(3)	(4)
Estimator	***unrestricted***	β_d*=1*	$\beta_d=\beta_n$	β_d*=0*
employment	0.69 (3.4)	0.70 (3.9)	0.70 (3.5)	0.68 (3.5)
capital stock	0.33 (2.5)	0.33 (2.4)	0.30 (2.2)	0.29 (2.1)
Returns to scale	1.02 (4.25)	1.03	1.00	0.97
days/worker	0.93 (2.4)	1.00 (imposed)	0.70 (imposed)	n.a.
Wald (γ_t)	17.6/7 (0.0)	17.4/7 (0.02)	19.3/7 (0.01)	20.7/7 (0.0)
σ^2	0.121	0.123	0.117	0.12
serial correlation(2)	0.70 (0.48)	0.78 (0.44)	0.46 (0.65)	-0.62 (0.53)
Sargan	56.5/57 (0.49)	56.7/58 (0.52)	60.2/58 (0.40)	37.2/43 (0.72)
Instruments	[e,k,d,w](2,4),γ_t	[e,k,d,w](2,4),γ_t	[m,k,w,d](2,4),γ_t	[e,k,w](2,4),γ_t

Notes: See notes to **Table 1.2**. The dependent variable is value added (y) except in column 2, where it is *value added per day (y-d)*. In column 3, output is regressed on *mandays (m)* and capital. Given n=employment and d=days, in logs, m=n+d. The restrictions in columns 2 & 3 were tested by including days/worker separately on the RHS. This gave **-0.7 (0.17)** in col.2 and **0.25 (0.75)** in col.3. Since these are insignificant, the restrictions are justified.

and its t-statistic, 0.75, provides a Wald test of the restriction. So, neither restriction can be rejected at the 5% significance level. However, the Wald tests and the changes in β_n and β_k induced by the restrictions suggest greater confidence in β_d=1. In column 4, *days* is dropped from the model, in keeping with other studies of Indian manufacturing. Although the GMM estimates in col.4 are similar to those in col.1, the former model is clearly misspecified since β_d is significantly different from zero in col.1 (t-statistic=2.4). It should

[8] Let y = β_nn + β_kk + β_d*days*. Imposing β_d=1 gives: (y-*days*) = γ_nn + γ_kk, where we expect that $\beta_n=\gamma_n$ and $\beta_k=\gamma_k$ if the restriction is valid. To obtain a formal test of the restriction, we run: (y-*days*) = γ_nn + γ_kk + γ_d*days*. If the absolute value of the t-statistic associated with γ_d is smaller than 1.96, then we cannot reject the restriction at the 95% confidence level. We find $|t|(\gamma_d)$=0.18, which gives us a comfortable margin.

be pointed out that if labour quality and multiple shift working are not adequately controlled for by a combination of fixed effects and time dummies, then the unrestricted estimate of the *days* coefficient is biased in the direction of the correlation of *days* with the omitted variables. On the other hand, given our somewhat unconventional interpretation of the factors behind *days* variation (see **Data Appendix**), it is not obvious that these correlations will be significant.

Some variants of the preferred model

Table 1.4 presents estimates of some variants. The *benchmark case* in column 1 is column 6 of **Table 1.2**. In column 2, we allow for *dynamics* (refer **Section 1.2.2**). Neither the

Table 1.4
Production Function Estimates: GMM
SOME VARIANTS

	(1)	(2)	(3)	(4)	(5)
Estimator/ Regressor	***GMM with external instruments***	***Allow dynamics***	***Impose CRS***	***Add (k-n)²***	***trend restriction***
$output_{-1}$		**-0.05 (0.5)**			
employment	0.69 (3.4)	0.45 (2.4)	**0.018 (0.11)**		0.77 (3.9)
$employment_{-1}$		**0.07 (0.7)**			
capital	0.33 (2.5)	0.40 (2.9)	0.33 (2.5)**	0.32 (2.1)**	0.34 (2.7)
$capital_{-1}$		**-0.09 (1.0)**			
$(k\text{-}n)^2$				**0.009 (0.9)**	
Returns to scale	1.02 (4.25)	0.85	1.02	1.00	1.11
days per worker	0.93 (2.4)	0.64 (1.7)	0.93 (2.4)	0.89 (2.6)	0.90 (2.8)
Wald (γ_t)	17.6/7 (0.0)	11.4/6 (0.08)	17.6/7 (0.014)	30.4/7 (0.0)	0.017 (1.8)***
Wald (RHS)	39.5/3(0.0)	43.6/6(0.0)	19/3 (0.0)		
σ^2	0.121	0.125	0.121		0.121
serial corr(2)	0.70 (0.48)	-0.58(0.56)	0.70 (0.48)	0.97(0.32)	0.65 (0.52)
Sargan	56.5/57 (0.49)	59.8/59 (0.45)	56.5/57 (0.49)	80.3/72 (0.23)	55.4/57 (0.54)
Instruments	[e,k,d,w](2,4) & γ_t	[n,k,d](2,4)w(2,3), y(3,4), γ_t	[n,k,d,w](2,4)γ_t	[n,k,d,w](2,4) & γ_t	[n,k,d,w] (2,4)& trend

Notes: See notes to **Table 1.2**. Column 1, the benchmark case is drawn from col.6 of Table 1.2. (**): In columns (3) and (4), read capital (k) as (k-n) and note that the dependent variable is (y-n) rather than y. (***):In column 5, instead of a Wald test on the joint significance of the time dummies followed by a p-value in parentheses, we have the coefficient on the trend followed by a t-statistic.

lagged dependent variable (y_{t-1}), nor lags of the inputs are significant, which is probably not surprising given that we have annual data. In column 3 we transform the production function to obtain a direct test on the *returns to scale* parameter. The Wald test on the restriction is 0.11, confirming that constant returns cannot be rejected. Imposing constant returns as in column 3, in column 4 we relax the Cobb-Douglas assumption by including the square of the *capital-labour ratio, $(k\text{-}n)^2$* (refer eq. 7). As this term is insignificant[9], we are led to conclude that the Cobb-Douglas specification is adequate. Column 5 reports the results of

Table 1.5
Production Function Estimates
EXPERIMENTS WITH INSTRUMENTS

	(1)	(2)	(3)	(4)
Estimator	***benchmark***	***n exogenous***	***k exogenous***	***d exogenous***
employment	0.70 (3.4)	0.69 (4.0)	0.56 (1.9)	0.74 (3.3)
capital	0.26 (1.7)	0.14 (0.83)	0.25 (2.5)	0.28 (1.8)
Returns to scale	0.96	0.83	0.81	1.02
days per worker	0.55 (1.1)	0.34 (0.6)	0.22 (0.35)	0.46 (2.8)
γ_t	18.9/7 (0.01)	24.2/7 (0.0)	53/7 (0.0)	17.8/7 (0.01)
σ^2	0.115	0.116	0.116	0.116
serial corr(2)	0.29 (0.77)	0.13 (0.90)	-0.27 (0.79)	0.17 (0.87)
Sargan	52.9/42 (0.12)	41.3/28 (0.05)	35.2/28 (0.17)	30.8/28 (0.32)
Instruments	[n,k,d] (2,4),γ_t	[k,d](2,4)Δn,γ_t	[n,d](2,4)Δk, γ_t	[n,k](2,4),Δd,γ_t

Notes: See notes to **Table 1.2**.

replacing the time dummies in the benchmark model with *a trend.* This creates an upward bias on β_n, leaving β_k and β_d more or less unaltered. Hence, aggregate productivity growth effects are not well captured by a linear trend and the resulting errors are positively correlated with employment. In **Table 1.5** we perform some experiments designed to determine whether a more parsimonious set of instruments is acceptable. Since the presence of external instruments may obscure the evidence we are looking for, we specify the

[9] This contrasts with Ahluwalia's (1991) finding well-determined quadratic and interaction terms in a translog model estimated by WG. However, the time series she uses is considerably longer than ours and so our results are not directly comparable.

benchmark case in column 1 as column 5 (and not column 6) of **Table 1.2**. In column 2, capital (K) and *days* are instrumented as before, but employment (N) is not. The Sargan statistic indicates that the residual is correlated with the instruments, which is not acceptable. So we must continue to instrument N. Column 3 reports the case where K is not instrumented. Although the instruments are valid, the Sargan difference statistic (col. 3 relative to col.1) is 17.7 (χ^2_{14}=23.7), which favours column 1. Finally, if K and N are instrumented while *days* is regarded as exogenous (col. 4), the Sargan difference is 22.1 which, again, is smaller than the critical value of 23.7. In conclusion, the validity of instruments for the other variables *requires* that employment be regarded as endogenous. While the equation diagnostics do not protest against the exogeneity of *K* and *days*, the Sargan difference test favours treating them as endogenous.

Summary of results

We now summarize what can be gleaned from our experiments with alternative estimators, and discuss the interesting features of column 6 of **Table 1.2**. There appear to be no significant *production lags* and the data reject the quadratic capital intensity term suggested by approximations to the *CES and translog functions*. Hence the estimates discussed refer to a static Cobb-Douglas production function. We find that the restriction of *time dummies* to a linear trend is not valid and, in our sample, produces upward biases on the output elasticities. There are significant *industry-state effects* on productivity and these time-invariant efficiency effects appear to be correlated with employment, capital and labour utilization. In addition, the **OLS** estimates appear to incorporate endogeneity and measurement error (ME) biases. The **GMM** estimates are known to avoid these biases. This gain comes with the disadvantage that the precision of the estimates is considerably lower. While the **WG** and **FD-OLS** estimates are not robust to endogeneity and ME biases, they nevertheless look reasonable.

The aggregate production function exhibits *constant returns* to scale, though the standard error on our estimate of the returns to scale parameter, at 0.24, is not negligible. When claiming constant returns estimated from a first-differenced model, it is important to add that the specification does not allow increasing returns arising from fixed start-up costs to show. The scale effects that we see are those realized as industries evolve through business cycles and regime changes. At approximately 0.7 and 0.3, the *output elasticities* of employment and capital are strikingly 'classical'. But over the period of this study, labour's share in value added (α) is 0.47. Therefore our estimates indicate *allocative inefficiency* or that, on average, workers are not paid their marginal product[10]. This 'exploitation' follows from imperfect competition in product markets, which can be characterized in terms of there being a positive markup of price on marginal cost. Equation (5) in **Chapter 4** can be recast as β_n=(1+markup)α or, equivalently, MP_N=(1+markup)(W/P) (also see Hall, 1986). By this, our estimates imply that *the markup* in Indian manufacturing is **48%**. Though it is associated with a large standard error, the unrestricted point estimate on average *days* is close to one, providing support for our theoretical hunch (refer **Section 1.2.1**). However, we have formally investigated the labour-augmenting restriction, $\beta_d=\beta_n$, against $\beta_d=1$. Wald tests on these restrictions indicate that the data cannot reject *either*[11]. Therefore, in the work that follows, we consistently allow both possibilities.

1.5. HETEROGENEOUS TIME-INVARIANT PRODUCTIVITY EFFECTS

Consider again, the results of using the different estimators presented in columns 1-3 of **Table 1.2**. The OLS-levels model (col.1) does not control for heterogeneity. In column 2, industry and state dummies are included and Wald tests on them indicate that the hypothesis of a common intercept cannot be accepted. Column 3 presents WG estimates which control for industry-state effects. The results are considerably altered. Two conclusions emerge: (a) there exist persistent differences in productivity levels across industries as well as states, and (b) industry and region effects interact. These results reinforce the view that there are important structural differences across the economy, which is one of the threads running through this thesis. The second is an important finding given that location is often neglected

[10] The output elasticity of employment, $\beta_n = \partial \ln Y/\partial \ln N = MP_N/AP_N$. The share of labour, $\alpha = WN/PQ = (W/P)/AP_N$. Thus, $\beta_n > \alpha$ implies $MP_N > (W/P)$.

[11] The Wald statistic associated with the restrictions is more favourable to $\beta_d=1$.

in studies of industrial productivity. Of course region effects are likely to be more important in a large country like India than in smaller countries. They are also likely to be more important in a developing economy where there can be vast differences between regions in infrastructure and human capital formation.

Table 1.6
Correlates Of State Fixed Effects On Productivity
Pearson Correlation Coefficients

Edu.	Literacy	Youth	Infrast.	Metrop.	Unempl.	Poverty	Dispute	Absent.
0.53 (p=5%)	0.47 (p=9%)	0.48 (p=8%)	0.43 (p=10%)	0.30 (p=12%)	0.38 (p=12%)	-0.31 (p=13%)	-0.33 (p=14%)	-0.15 (p=12%)

Notes: Figures in parentheses are the p-values associated with the estimated coefficients. *Edu.*=proportion of the population with higher education, *Literacy*=proportion literate, *Youth*=proportion of 15-29 year olds, *Infrast.*=index of infrastructural development, *Metrop.*=dummy for Delhi, Maharashtra, W.Bengal and Tamil Nadu, *Unempl.*=unemployment rate (coefficient is the same for usual and daily status rates), *Poverty*=proportion below a poverty line, *Dispute*=fraction of workers involved in disputes, *Absent.*=absenteeism rate.

Industry-state efficiency effects are recovered from the GMM estimates of the production function by a method similar to that described in Part 4 of **Chapter 3**. Taking output-weighted averages, we obtain industry and state effects. The state effects are regressed on some of the regional variables identified in **Chapter 2**. Results are set out in **Table 1.6**[12]. State efficiency levels are significantly positively correlated with educational levels in the work force (*edu., literacy*) and, somewhat surprisingly, positively correlated with the proportion of young in the population (*youth*). One might conclude that agility counts more than experience but this would be hasty as this is merely a correlation and it may reflect, for instance, a positive correlation of youth and literacy. The 'structural' determinants of productivity levels are agglomeration effects' (*metropolis*) and infrastructural development (*infrastr*), which displays considerable variation across states (CV=37% in 1972 and 29% in 1987; based on CMIE data). The fact that average manufacturing productivity is higher in states with relatively high unemployment rates (*unempl.*) might be interpreted as evidence of an efficiency wage effect. The idea is that the fear of unemployment outside stimulates

[12] Variables are defined in Table notes and further details are in the **Data Appendix**.

'unobservable' effort on the part of workers. A negative association of poverty incidence (*poverty*) and productivity is most likely an artefact. One might argue that it reflects the fact that less well-fed populations cannot work very hard (ref. the modified nutrition-efficiency wage hypothesis, **Chapter 6**). This argument is weakened by the fact that only a small fraction of the state population is in the factory sector, to which the productivity measure refers. States where a larger fraction of the factory work force is involved in industrial disputes (*dispute*) appear to have had lower productivity, and similarly, *absenteeism* has a negative impact on productivity. It should be emphasized that, as demonstrated by the *p-values* in **Table 1.6**, many of the reported correlations are only weakly significant[13] Finally, it may be worth noting that correlations of the efficiency effects with the *left-wing* dummy, *public sector* concentration and *union density*, were completely insignificant.

1.6. INDUSTRY-SPECIFIC TECHNOLOGIES

It has, so far, been assumed that the production function elasticities are common across manufacturing although the intercept is sector-specific. In fact, however, the slope coefficients may differ, for example because certain industries exhibit increasing returns to scale.

1.6.1. Method

We investigate industry technologies using pooled state-year data, which gives 120 observations once the FD or WG transformation is effected. There are too few cross-sectional observations (15 states) for reasonable GMM estimates. Therefore, the equations are estimated by both FD-OLS and WG. These estimators are subject to biases arising from measurement error (ME) and endogeneity (**Section 1.3.1**). Under the assumption that only capital is measured with error, the ME bias is eliminated by employing the Griliches-Hausman corrections described in equations (17). The *corrected estimates* remain afflicted with endogeneity biases. However, the results obtained on the aggregate sample indicate that

[13] Often, the variation in the data is rather small. For example, the standard deviation of log *absenteeism* is only about 13%.

these are unlikely to be very serious (**Section 1.4**). Indeed, comparing columns 3-4 with column 6 in **Table 1.2** indicates little change in the coefficient on employment. The *days* coefficient does change considerably. We get around this problem by restricting its coefficient as explained below.

1.6.2. Results

Layout

The estimated production function parameters are in **Table 1.7**. There are three sets of estimates corresponding to three alternative restrictions on the *days* coefficient, namely, $\beta_d=1$, $\beta_d=\beta_n$ and $\beta_d=0$. On the basis that any ME and endogeneity biases are smaller in WG than in FD-OLS, we report WG coefficients[14]. *Corrected estimates* appear just below the WG estimates in a given cell. As expected, the ME-bias corrections produce larger capital coefficients and smaller employment coefficients. In employing (17) to perform the corrections, we found that, for some industries, the estimated variance of the (assumed) measurement error was negative. Since this violates the assumption of ME, the correction is not made for these industries. Corrections are not attempted for the case $\beta_d=0$ because this model is misspecified in any case. In column 8, we present the average share of labour in the industry (α). Except in electricity and petroleum-rubber, it is considerably smaller than the output elasticity of employment [in columns 1 & 3], confirming the result obtained with the aggregate sample. For ease of reference, the *preferred* estimates alone (*corrected* where available, WG otherwise) are in **Table 2.8** in **Part 2**.

The final factor coefficients

Refer **Table 2.8**. In 4 of the 18 industries, the final estimate of capital productivity is rather small and these are cases where it was not possible to correct for ME-bias. The *downward* ME-bias corrections to the employment coefficients (see (16)) are typically modest and they remain implausibly large in almost half of the industries. It is doubtful that this reflects

[14] On the relative size of ME biases under different estimators, see **Section 1.3.1**, equations 15. The relative size of endogeneity biases is governed by the same principle.

Table 1.7
INDUSTRY TECHNOLOGIES
Within Groups and Corrected Estimates

	β_d=1 Corrected est. in lower row			β_d=β_n		β_d=0		Some data
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Industry	β_n	β_k	RTS	β_n	β_k	β_n	β_k	α
Miscellaneous	0.70 0.61	0.17 0.35	 0.96	0.82	0.06	0.64	0.20	0.39
Petroleum & rubber	0.29	0.31	0.60	0.07	0.39	-0.03	0.41	0.41
Food products	0.94	-0.18	0.76	0.64 0.58	-0.13 0.04	0.36	-0.05	0.23
Cement, glass etc	1.02 0.96	0.12 0.22	 1.18	0.74	0.16	0.92	0.16	0.42
Tobacco & beverages	0.78 0.77	-0.02 0.12	 0.89	0.40 0.39	0.013 0.10	0.29	0.02	0.38
Electrical machinery	0.95 0.87	0.16 0.19	 1.06	0.90	0.18	0.24	0.33	0.44
Wood & furniture	1.43 1.39	-0.02 0.08	 1.47	0.25	0.24	0.74	0.16	0.48
Metal products	1.07	0.06	1.13	1.00 1.00	0.08 0.08	1.07	0.06	0.53
Non-elec machinery	1.05	0.16	1.21	0.87 0.86	0.32 0.34	0.91	0.21	0.30
Paper & publishing	0.77	0.05	0.82	0.99 0.99	-0.02 -0.02	0.77	0.05	0.44
Transport equipment	0.98 0.95	0.28 0.36	 1.31	1.05 1.02	0.28 0.37	0.91	0.28	0.39
Chemical products	1.75	0.03	1.78	1.50	0.09	1.17	0.28	0.44
Textile products	0.92 0.90	0.15 0.18	 1.08	0.99 0.98	0.12 0.13	0.89	0.17	0.37
Wool & silk textiles	0.81 0.73	0.24 0.40	 1.13	0.49	0.36	0.73	0.29	0.40
Cotton textiles	0.70 0.61	0.20 0.36	 0.97	0.88 0.77	0.13 0.31	0.67	0.26	0.50
Leather & fur	1.09	0.29	1.38	0.99	0.34	1.03	0.27	0.37
Basic metals & alloys	0.75 0.64	0.31 0.45	 1.09	0.77 0.64	0.31 0.46	0.67	0.37	0.42
Electricity generation	0.00	0.74	0.74	0.03 0.03	0.74 0.74	-0.02	0.78	0.64
Manufacturing	0.75 0.73	0.18 0.21	 0.94	0.58 0.57	0.24 0.26	0.51	0.26	0.465

Notes: Numbers in the lower row of each cell in col.1-3 are corrected for measurement error biases.

primarily an endogeneity bias (refer columns 4-5 against 6 in **Table 1.2**). Instead, we suspect that it is a consequence of *hoarding*. **Table 1.8** sets out a tree-structure of situations in which industries in our sample may have found themselves. Consider a shrinking industry in *situation (1)* which is losing employees but not fast enough, for example, because there

Table 1.8
The Bias On The Employment Coefficient
A Tree of Possibilities

Negative employment growth		**Positive employment growth**	
(1)	(2)	(3)	(4)
Hoarding	*Dehoarding*	*Hoarding*	*Dehoarding*
overestimate	underestimate	underestimate	overestimate
restrictions on firing	no restrictions on firing	politically determined targets	cost-consciousness under competition

Notes: The items in the last row are only examples of factors that may underpin the situation described.

are restrictions on firing. These may be legal or imposed by unions[15] but, in any case, they result in 'involuntary hoarding' of workers. As an example, if the true β_n=0.5 and Δy= -1%, then desired Δn= -2% but actual Δn= -1% p.a., giving estimated β_n=1.0, which is an over-estimate. Now consider a growing industry in *situation (4)*. This is the prototype considered in **Chapter 4**, Section 6.4. Suppose, again, that true β_n=0.5 but now Δy= 1%. Then desired Δn= 2% but, because the industry is carrying hoarded labour from the preceding period, it chooses actual Δn= 1% so as to start dehoarding, for example because it must cut costs to compete. Again β_n will be estimated as 1.0, which is an over-estimate. Situations (1) and (4) are compatible with the story spun in **Chapter 4** as there seemed to have been either straight losses in employment or a process of dehoarding in most parts of the factory sector in the 80s. However, *situation (3)* may describe some important exceptions, of which the electricity industry seems most illustrative (see **Table 2, Chapter 4**). This is a situation of 'voluntary hoarding', for example, to meet employment targets set in public sector industries. So, for Δy= 1%, if desired Δn= 2%, here we would observe, say, actual Δn= 3%,

[15] A less considered alternative explanation of slow downward adjustment of employment is that it may just take long for the production process to adjust to the 'lower' equilibrium, i.e, you may be able to release 1000 men in the long run, after some reorganization, but you couldn't spare them all at once in the short run.

and β_n would be under-estimated. It is rather striking that our estimate of β_n in electricity is close to zero. This is the classical *surplus labour* case. So either the public sector 'absorbs' workers in the manner that ones own land is deemed to, or there is some gross mismeasurement here.

There are several studies, most of which pertain to the U.S. or the U.K., that have estimated a coefficient on employment that exceeds unity (Kuh 1965, Brechling 1965, Brechling and O'Brien 1967, Ball and St Cyr 1966, Coen and Hickman, 1970). Some of these have proposed, like us, that, if there is labour hoarding, then theoretical decreasing returns to labour can be reconciled with the finding of increasing returns. Others have suggested that the empirical finding is consistent with variable rates of capacity utilization in a scenario where technology is putty-clay (see Craine, 1973).

Returns to scale (RTS)

The RTS estimates in column 3 of **Table 1.7** refer to the corrected estimates where these are available and to the WG estimates in the residual cases. Since the standard error of the

Table 1.9
Industry Returns to Scale

Assumption	CRS (0.76-1.24)	DRS (<0.76)	IRS (>1.24)
(A) β_d=1	misc, *food*, cem, *tob*, elm, met, mach, pp, txp, wstx, ctx, fe (N=12) & MFG.	pet, *elec* (N=2).	*wood*, transp, chem, lea (N=4).
(B)β_d=β_n	misc, cem, elm, met, mach, pp, txp, wstx, ctx, fe, *elec* (N=11) & MFG.	pet, *food*, *tob*, *wood* (N=4).	transp, chem, lea (N=3).

Notes: The italicized names refer to industries which fall into different classifications under the alternative assumptions, A and B. The industry count in each cell is labelled N. *Source:* **Table 1.7**. *Abbreviations:* CRS=constant returns, DRS=decreasing returns, IRS=increasing returns, β_d=*days* coefficient. The industry acronyms are: misc=miscellaneous; food=food products; cem=cement, glass, etc.; tob=tobacco & beverages; elm=electrical machinery; met=metal products; mach=non-electrical machinery; pp=paper & printing; txp=textile products; wstx=wool & silk textiles; ctx=cotton textiles; fe=basic metals; pet=petroleum & rubber; elec=electricity; wood=wood products; transp=transport equipment; chem=chemical products; lea=leather & fur; MFG=manufacturing.

RTS estimate for aggregate manufacturing is 0.24 (col.6, **Table 1.2**), for simplicity, an industry is deemed to have CRS technology if its RTS lies between 0.76 and 1.24. This criterion generates the distribution displayed in **Table 1.9**. Two-thirds of the industry groups exhibit CRS. Irrespective of the assumption made about *days* effects, transport equipment, chemicals and leather & fur show potential for scale efficiencies. This is consistent with engineering studies of technology which, for industrial countries, have identified a potential for IRS in transport and chemicals, in addition to basic metals, metal products and electrical machinery (Berry 1992, Scherer and Ross 1990). Under both assumptions, petroleum & rubber, which absorbed the largest share of public investment in the 1980s (Ahluwalia 1991, p.87) and which was the most rapidly expanding sector in this decade (**Table 2, Chapter 4**), shows decreasing returns. These rather orderly results are subject to two qualifications. First, the clustering around RTS=1 may be a 'coincidence' arising from under-estimation of β_k along with over-estimation of β_n, at least for a part of the sample. Second, industry variation in returns to scale would be greater were the industry groups more disaggregated. For instance, Westbrook and Tybout (1993) find that RTS for Chilean industry are scattered across the range 0.8-1.2 at the 3-digit level and 0.7-1.6 at the 4-digit level.

PART 2

TOTAL FACTOR PRODUCTIVITY GROWTH: ESTIMATES AND ELEMENTS

Estimates of the production parameters obtained in **Part 1** describe scale and allocative efficiency. In this section we are concerned with measurement of gains in technical efficiency. This is topical in India, where there is evidence of a turnaround in productivity growth in the early 1980s that marks the first real improvement in efficiency since planned development was implemented in 1951. Since the work of Ahluwalia (1991), it is popularly believed that the turnaround can largely be attributed to changes in the economic regime that started at the turn of the decade. Given less than unanimous support for the 'new economic policy', its future course remains open to debate and any evidence of its impact is eagerly devoured by policy-makers and the press. Therefore the evidence must be looked at carefully. This section offers estimates of TFP growth (henceforth **TFPG**) that we believe are more reliable than any existing estimates. Our contribution is primarily methodological. With a larger sample and more disaggregate data, the suggested method will yield even more reliable numbers. The productivity performance of Indian manufacturing since Independence is reviewed in **Section 2.1**, together with a brief recapitulation of the better accepted causes of poor performance. We then consider a perspective on features of growth and productivity peculiar to less-industrialized countries (**Section 2.2**). The method and results of estimating TFPG for aggregate manufacturing sector are described in **Section 2.3**, followed by a consideration of elements that we think may have contributed to the pick-up in TFPG. Finally, in **Section 2.4**, we present estimates of TFPG for each of 18 two-digit sectors. On account of the tighter data constraint at the industry level, some differences in method arise, as compared with Section 2.3, and these are pointed out.

2.1. THE PRODUCTIVITY RECORD IN INDIAN MANUFACTURING

Krishna (1987) surveys the corpus of studies of productivity in Indian manufacturing during a part or all of the period, 1950-1980. While agreement between the precise numbers is scarce, the basic result is that, on average over the entire period, productivity growth was negligible (**Table 2.1**), but there was a marked acceleration in the early 1980s. Using consistent methodology (the Solow index) for different sub-periods of 1959-85, Ahluwalia (1991) demonstrates the turnaround.

Table 2.1
The TFPG Record in Indian Manufacturing: Estimates of Different Authors

Sector	**Author**	**Period**	**TFPG**
Registered	Ahluwalia (1985)	1960-80	-0.6
	Brahmananda (1982)	1950-80	-0.2
	Banerji (1975)	1948-64	-1.6
Large-scale registered	Mehta (1980)	1959-70	-1.6
Large-scale registered + Electricity	Goldar (1986)	1959-79	1.3
Small-scale registered	Goldar (1986)	1960-78	1.2
Unregistered	Brahmananda (1982)	1950-80	-1.0

Notes: Brahmananda's estimates are based on the Kendrick index of TFP [$TFP_K=Y/(wN+rK)$] and the others, on the Solow index (see **Section 2.3.1**). Sector definitions in the **Data Appendix**. *Source:* Adapted from Ahluwalia (1991), Table A, p.65.

Turning to **Table 2.2**, there was rapid industrial growth during Periods I and II, followed by 'industrial stagnation' in Period III. In the 1980s, industrial growth recovered (refer column 1, **Table 2.5**). The course of productivity was somewhat different. In Period I, there was positive growth (Goldar (1983): 2.8% , Banerji (1975): 2.1% p.a.). While output growth continued unabated, TFPG slowed down after 1956 (Goldar (1983): 0.8%, Banerji (1975): -4.1% p.a.). It then remained negligible until the recovery of the 1980s. The only TFPG estimates for Period IV are those of Ahluwalia (1991). Using the Solow index, she computes TFPG in 1980-85 as 3.4% p.a. (Chapter 2, p.76) but her estimate of the trend coefficient in a production function lies between zero (Cobb-Douglas) and 0.6% (Translog) per annum (Chapter 6, p.157). Surprisingly, there is *no* discussion of this discrepancy.

Having summarized the evidence, we turn to a brief consideration of the factors deemed to have determined the course of productivity growth. Periods 1 and 2 are demarcated by a significant increase in investment after 1956, accompanied by a massive inflow of foreign technology embodied in new capital goods. The deceleration in productivity after 1956 is attributed mainly to a fall in the rate of capacity utilization (Goldar, 1983).

Table 2.2
Growth in Output and Productivity: 1950-87
A Schematic Representation

Period	**Output growth**	**TFPG**
I. 1951-56	high	high
II. 1956-65	high	low
III. 1965-78	low	low
IV. 1980s	high	high

Source: Author's construction based on discussion in Goldar (1983). Numbers are not presented because no one author has produced estimates for these four periods, and estimates of different authors are typically not comparable.

Considerations of the causes of negligible productivity growth between 1956 and 1980 mostly appear as appendages to analyses of the slow growth of output in this period. These studies have focused on the consequences of the industrial policy framework for both the structure of the economy and the incentives it generates (Bhagwati and Desai (1970), Bhagwati and Srinivasan (1975) and Ahluwalia (1985)). In a meticulous survey of the literature, Ahluwalia (1985) identifies three factors that contributed to stagnation of output growth during 1965-78. These are (i) low levels of investment and efficiency in the infrastructure sectors (ie., railways, electricity and coal) (ii) restrictive industrial and trade policies and (iii) the slow growth of per capita agricultural income. In her 1991 study, she attributes the turnaround in productivity growth in the 1980s to a considerable relaxation of the constraints (i) and (ii). For this reason, it is worth looking more closely at these two factors and their development from Period III to Period IV.

Infrastructure

While infrastructural investment contributes to the demand for capital goods, its supply effects are probably more crucial for overall economic growth. Frequent shortages of fuels, power and transport facilities caused by low investment and efficiency in the infrastructural sector contributed significantly to the creation of excess capacity in Indian factories in the two decades prior to 1980 (Ahluwalia 1985, for example). While there was an overall decline in public investment in the mid-60s, this fell disproportionately upon the infrastructure sectors.

Table 2.3
INVESTMENT IN INFRASTRUCTURE
Sub-period growth rates

	1960-65	**1965-75**	**1975-79**	**1979-84**	**1985**	**1986**
growth rate	15.0	4.2	5.4	9.7	16.0	18.3
share (%) in total I	39.8	33.9	34.3	40.4	42.3	46.9

Notes: The data refer to gross domestic capital formation at 1980 prices and growth rates are obtained as annual averages. *Infrastructure* includes power, railways and mining. *Source:* National Accounts Statistics, 1989 and 1990.

Investment deficiencies were compounded by inefficiencies in allocation. For example, transmission losses of electricity were 17% in the late 60s and more than 20% in 1980 (Central Electricity Authority). Political interference by State Electricity Boards in management and hiring practices was a powerful drag on their efficiency (Government of India, 1982). The story of the railways is similar in its broad outline. During 1965-79, the railways sector registered declining efficiency in terms of physical indicators such as engine speed and net tonne kilometres moved per tonne of wagon capacity. These were largely attributed to neglect of maintenance and technological upgrading. The efficiency of thermal power plants suffered on account of coal shortages stemming from transportation bottlenecks for bulk commodities (Railway Board). Investment in power and railways picked up in the 1980s (**Table 2.3**). Thus, the power deficit came down steadily from 16% in 1979 to 6.7% in 1984 (Central Electricity Authority). Along with more resources being devoted to the Railways, there were improvements as regards planning and co-ordination, and the physical indicators registered the benefits (Railway Board). Evidence of improved efficiency in Electricity is limited[16]. While there was no fundamental reorganization, capacity utilization in generators rose. Having declined from 56% in 1976 to 45% in 1980, the plant load factor rose steadily to 57% in 1987 (Ahluwalia, 1991). However, in the medium term, manufacturing productivity depends upon the supply of infrastructure and considerations of whether better supply arose from more investment or more efficiency are secondary.

[16] This is why we include Electricity in our sample. See **Section 2.4.2**.

Policy

In general, pursuit of the objectives of self-reliance, regional dispersal of industry and dispersal of economic power was accompanied by neglect of efficiency. Industrial licensing and import substitution were the principal instruments designed to meet these objectives. In addition, certain industries have, at different times, been subject to price and distribution controls. Indian entrepreneurs had to face sequential clearance hurdles that cumulated in uncertainties, long delays, and often, idle capacity[17]. Controls and rations encouraged rent-seeking on so large a scale that the associated deadweight loss is estimated to have been as much as 40% of GNP (Mohammed and Whalley, 1984). Thus, indications of *over-capitalization* identified in **Section 1.4** may be interpreted as symptoms of rent-seeking behaviour. Perhaps more serious, the licensing system created entry barriers to industries. Coupled with import substitution, this resulted in a stifling of competition. A 'soft attitude' towards sick industries further reduced incentives for cost-consciousness. Restrictions on technology imports led, *inter alia*, to inefficient use of materials, especially energy. The Monopolies and Restrictive Trade Practices Act and the Foreign Exchange Regulation Act restricted expansion of large firms and at the same time, various products were reserved for small scale production. Together these interventions compromised scale economies and are responsible for the development of a high-cost low-quality manufacturing sector in India. Stagnation in industrial growth from the mid-60s to the mid-70s provoked a reorientation of policy, which started in the late 1970s and gained direction in the 1980s[18]. The most important change was a reduction in barriers to entry and expansion, which resulted in an increase in domestic competition. In addition, import restrictions were weakened, implying easier access to intermediate inputs and technology. Even though deregulation in the 1980s was a halting process, it marked a significant change in the economic 'culture'.

[17] See, for instance, GOI (1967, 1969, 1979) and Jha (1980).

[18] An account of changes in the policy framework is provided, for example, in a document produced by the Centre for Monitoring of the Indian Economy (CMIE, 1991), Kelkar and Kumar (1990) and Ahluwalia (1991).

2.2. TOTAL FACTOR PRODUCTIVITY IN LESS INDUSTRIALIZED ECONOMIES

On the grounds that less industrialized economies (henceforth, *LIEs*) are 'supply determined', economic development is commonly defined as a process of improving the productive capacity of the economy. This can be done by increasing investment or efficiency, especially in bottleneck areas. The industrialization strategies of most developing countries, including India, have concentrated on raising investment, to the relative neglect of efficiency. As a result, 'the two most striking characteristics of LDCs, which largely account for their low per capita income, are the *under-utilization* and the *inferior productivity* of their land and labour resources' (Eshag, 1991).

Since the mid-70s, a large body of evidence on the role of TFPG in economic growth has accumulated. A notable contribution in the developing country domain is that of Nishimizu and Page (1987), who have assembled two-digit industry data for 18 countries in 1956-82, of which 14 are LDCs. Chenery *et al* (1986) find similar patterns when studying macroeconomic data for 18 industrialized and 12 industrializing economies in the 60s and 70s. Together, their estimates of TFPG show that productivity growth in LIEs is more rapid than in the mature industrialized economies (IEs), and its contribution to output growth is smaller. Higher rates of productivity growth are probably a reflection of gains in technical efficiency arising from the mastery of technology, added on to the gains from actual technical progress (see Westphal, 1981 and Nishimizu and Page, 1982 for a contextual discussion). During 1956-82, productivity change contributed 10-30% of output growth in LIEs, with the exception of Zambia, India and the Philippines, which had negative TFPG. The rapidly growing middle-income economies, including Japan, Hong-Kong, Taiwan, Israel and Spain broadly fitted the LIE pattern. In IEs, excluding Japan, the rate of TFPG was only about 1% p.a. and is regarded as approximating the long run rate of technical progress. Yet, its contribution to economic growth was substantial, at about 50%. As we shall see, *India's experience in the 1980s appears to challenge the IE/LIE dichotomy.*

A further distinguishing feature of LIEs is the existence of large inter-industry and inter-country variability in TFPG. The persistence of inter-sector productivity differentials in LIEs possibly reflects the greater rigidities in factor mobility in economies at early stages of market development. Resources may not move so easily out of lagging and into leading industries or regions, and processes like skill diffusion take time. This is especially true for regions. Industrial development is a 'regionally sporadic' process. In India this is, very likely, reinforced by increasing returns effects arising from the non-uniform regional spread of public investments in infrastructure. While the *IE-LIE* differences appear to be 'structural', Nishimizu and Page (1987) argue that the high degree of variation observed *within* the group of LIEs points to policy-based explanations. In fact, there are different stages of development within the LIE group, and measurement error may explain a part of the divergence, so policy conclusions should be drawn with some caution.

2.3. ESTIMATES OF TFPG FOR AGGREGATE MANUFACTURING

2.3.1. Method

The Regression Method

It is useful here to recall the form of the production function estimated in **Part 1**:

$$\Delta y_{ist} = \beta_n \Delta n_{ist} + \beta_k \Delta k_{ist} + \beta_d \Delta days_{ist} + \theta_t + \theta_0 + \Delta e_{ist} \qquad (19a)$$

θ_t is obtained by differencing τ_t, the time dummies in the levels model. These pick up growth in total factor productivity. Denote $\kappa_t = \theta_t + \theta_0$ for each t. Then κ_t are the yearly growth rates. To obtain a smoothed trend growth rate for the period, we 'reclaim' the τ_t from the κ_t by setting $\kappa_{1979}=0$ and cumulating. The τ_t are then regressed on a linear trend and the trend coefficient is an estimate of p.a. TFPG. Year-specific blips in efficiency are strait-jacketed if the time dummies are replaced by a linear trend in (19a). Yet, the trend restriction is investigated both because it is employed by Ahluwalia to produce the only existing estimate of the 1980s growth rate in India and because it is an option we might like to consider when faced with a degrees of freedom problem in estimating industry-specific TFPG. Corresponding to different restrictions on β_d, we derive different estimates of TFPG.

(a) Factor shares: The Solow index

The traditional Solow index that is most commonly used to estimate TFPG is

$$\Delta \mathbf{tfp}_{\mathbf{Solow}} = \Delta y - \alpha\Delta n - (1\text{-}\alpha)\Delta k \tag{21a}$$

where the variables are in logarithms and α is the share of labour in value added. Existing studies for India estimate (21a) with n=employees, implicitly setting β_d=0. We estimate (21a) for purposes of comparison, using a period-average of α, rendering it a constant. Both Solow (1957) and Abramowitz (1950) measured employment (*n*) as total manhours worked, so assuming that hours is labour-augmenting (ie, $\beta_d=\alpha$)[19]. In view of our results in **Section 1.4**, we also entertain the possibility that β_d=1. Under the alternative assumptions, $\beta_d=\alpha$ and β_d=1, we obtain two further Solow measures of TFPG:

$$\Delta \mathbf{tfp1}_{\mathbf{Solow}} = \Delta y - \alpha\Delta m - (1\text{-}\alpha)\Delta k \tag{21b}$$

$$\Delta \mathbf{tfp2}_{\mathbf{Solow}} = \Delta(y\text{-}days) - \alpha\Delta n - (1\text{-}\alpha)\Delta k \tag{21c}$$

In (21b), *m*=total *mandays*. So, in logarithms, m=(n+*days*). (21b) is the most natural formulation when α is the share of labour in value added. However, (21c) may be a closer approximation to the actual production function.

(b) Marginal products: The modified Solow index

The Solow formulation assumes perfectly competitive product markets. Were this true, the factor shares observed in the data would provide an adequate measure of the contributions of the factors to value added. However, we have established in **Part 1** that the contribution of labour to output exceeds its share by almost 50%. Therefore we use estimated production function elasticities in place of factor shares. This relaxes not only the assumption of perfect competition but also the assumption of constant returns to scale that is implicit in (21).

[19] Average hours per worker in our data is given by a constant multiple of days worked per worker (*days*). See **Data Appendix**.

Neglecting *days*, the modified index of TFPG is

$$\Delta \mathbf{tfp}_{MP} = \Delta y - \beta_n \Delta n - \beta_k \Delta k \tag{22a}$$

where MP=marginal product and the β's are estimated output elasticities. Purging *days* effects under the alternative restrictions $\beta_d=\beta_n$ and $\beta_d=1$ gives

$$\Delta \mathbf{tfp1}_{MP} = \Delta y - \beta_n \Delta m - \beta_k \Delta k \tag{22b}$$

$$\Delta \mathbf{tfp2}_{MP} = \Delta(y\text{-}days) - \beta_n \Delta n - \beta_k \Delta k \tag{22c}$$

where notation is as in (21) and β_n and β_k are not the same in equations (22a-d), but are estimated from regressions incorporating the different restrictions on β_d. Of course, equations (22) give the same results as the regression method.

2.3.2. Aggregate Results

Estimates of TFPG

Estimates of productivity growth in manufacturing during 1979-87 are presented in **Table 2.4**. Row A reports TFPG rates obtained holding *days* constant and Row B reports estimates obtained under the mistaken assumption that $\beta_d=0$. So Row B is reported only to demonstrate the degree of error in existing TFPG estimates for Indian industry[20]. The traditional Solow algebra (eq.21) yields column (1) and the modified algebra, eq.(22), gives columns 2-4. The output elasticities (β's) employed in column 2 arise from a production function estimated by WG, while those in columns 3-4 are GMM estimates.

The traditional Solow index considerably under-estimates TFPG. This is easily explained with reference to our data. The trend growth in employment over the period under consideration is close to zero. Therefore, the bigger the estimated marginal product of

[20] Denote $[y-\beta_n^A n-\beta_k^A k-\beta_d days]=TFPG^A$ and $[y-\beta_n^B n-\beta_k^B k]=TFPG^B$, where the superscripts refer to the rows A and B in the Table. Then $TFPG^B-TFPG^A = [\beta_d days + (\beta_k^A-\beta_k^B)k + (\beta_n^A-\beta_n^B)n]$. So, the error is due not only to omitting the contribution of *days* to output growth, but also to mismeasuring β_n and β_k by not controlling for *days*.

capital, the smaller is the estimate of TFPG. But the Solow index uses factor shares and we have seen (**Part 1**) that capital 'earns' more than its marginal product[21]. We regard column 4, row A as the *'preferred estimates'*. Consider the other estimates in row A relative to these. Column 3 demonstrates that restricting time dummies to a linear trend generates a biased estimate of TFPG, because the input coefficients are biased (see col. 5, **Table 1.4**).

Table 2.4
TOTAL FACTOR PRODUCTIVITY GROWTH
Estimates for Aggregate Manufacturing

	Value added shares	Elasticities of value added with respect to the inputs		
		Within groups	GMM with trend	GMM with time dummies
	(1)	(2)	(3)	(4)
(A) TFPG exclusive of days	(a) 1.1 (b) 1.9	(a) 3.6 (b) 3.8	(a) 2.2 (b) 2.8	**(a) 2.4 (b) 3.8**
(B) TFPG inclusive of days	2.7	4.6	3.9	**4.5**

Notes: In row A, col.2-4, (a) restriction: β_d=1, (b) restriction: β_d=β_n. In row (B), β_d=0, where β_d is the *days* coefficient.

Column 2 presents the numbers obtained when the production function is estimated by WG. This is interesting because, for reasons discussed in **Section 1.6**, the industry-specific production functions are estimated by WG. Our investigations in **Part 1** (**Table 1.2**, col.3 and 6) showed that, relative to GMM, the WG estimates are similar for β_n, somewhat smaller for β_k and a lot smaller for β_d. As far as β_n is concerned, not only is the discrepancy small but for purposes of calculating TFPG it matters least since, in our sample, trend employment growth is close to zero. Turning to the WG estimate of β_k, we have the tools to institute an upward correction (see equation 17, **Section 1.3.1**). In order to deal with the bias in β_d, we impose the restrictions β_d=1 (which gives (a)) and β_d=β_n (which gives (b)). These restrictions were investigated (using the GMM estimator) in **Part 1** (**Table 1.3**) and

[21] In row B, column 1, where we obtain 2.7%, the other available estimate for India is 3.4% by an identical method (Ahluwalia, 1991). Investigation of this difference suggests that it stems from our having somewhat different estimates of the trend rates of growth of all three variables even though definitions and deflators appear to be well-matched between the two studies. Unfortunately, though ameliorated, this difference persists even when we restrict our sample to match Ahluwalia's (1980-85).

it was found that they could not be rejected. *With $\beta_d=1$, WG 'overestimates' TFPG by 1.2%-points* (3.6% against 2.4% using the GMM elasticities). *With $\beta_d=\beta_n$, WG and GMM give virtually identical growth rates.* In view of our discussion in **Section 1.4 (Table 1.3)**, $\beta_d=1$ is our favoured assumption. So our *best estimate* of TFP growth in manufacturing is 2.4% p.a. However, given that we cannot reject $\beta_d=\beta_n$, we put the final estimate in the range, 2.4-3.8% p.a.

The contribution of productivity to output growth

Since value added was growing at a trend rate of 6.3% p.a. in real terms, the contribution of TFPG to output growth is in the region of 36 to 60% (col. 4, **Table 2.4**) and trend growth in *days* at 1.64% p.a. over the period contributed an *additional* 26% to 18%, depending on what is assumed about the place of days in the production function. This is remarkable not only relative to India's past record (**Table 2.1**), but also relative to the experience of other low income nations, at least up to the early 1980s (**Section 2.2**).

2.3.3. Behind the Rise in TFPG

The acceleration in TFP is probably partly a *composition effect* flowing from the exit of less efficient firms following some dismantling of protection mechanisms in the 1980s. Although the two effects cannot be disentangled when we have industry and not firm data, it seems that there was also a gain in efficiency at the firm level. This appears to have been on account of a complex of changes associated with *increasing competition* and *rising output* in this period. The idea that output growth begets productivity growth is now entrenched as Verdoon's law (Verdoon, 1949). It has been upheld by empirical investigations in several countries, and by Goldar (1987) and Ahluwalia (1991) for India, using time series data on industries. Theory and evidence pertaining to the view that competition encourages productivity growth is discussed in Nickell (1993) and the view that Indian industry faced more intense competition in the 1980s than before is discussed in Section 6.4 of **Chapter**

4. (Also see **Section 2.1** above)[22]. To complement that discussion, we now consider the *manner* in which competition and growth may have operated to raise productivity growth.

The Solow formula can be recast in terms of partial productivities as

$$\Delta tfp = \beta_n \Delta(y-n) + \beta_k \Delta(y-k) \tag{24}$$

With reference to **Table 2.5**[23], it is clear that acceleration in TFP in the 1980s was *mostly* on account of a considerable jump in the growth rate of *labour productivity*, although an arrested decline in *capital productivity* did contribute. The fact that $\beta_n > \beta_k$ reinforces this. So, the critical question is: How was more output produced with less employees? We believe that the following are important factors: (a) an increase in observable effort, (b) an increase in unobservable effort and (c) 'modernization' of capital stocks and upgradation of

Table 2.5
Total and Partial Productivities
Sub-period Growth Rates

	value added	total factor productivity	labour productivity	capital productivity
1959-65	9.1	0.2	4.9	-3.8
1965-79	5.0	-0.3	1.4	-1.9
1980-85	7.5	3.4	8.3	0.0

Source: Adapted from Ahluwalia (1991), Table 3.2. *Notes*: All figures are in percentages. The TFP growth rates refer to the traditional Solow index (using factor shares) and *days* is not held constant.

technology. The last has been noted by several authors concerned with policy changes in the 1980s (eg., Ahluwalia 1991,p.92). The possibility that increased *effort* on the part of workers could have been instrumental in the productivity turnaround seems to have escaped

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[22] A further 'structural shift' associated with the 1980s is an increase in *subcontracting* (see Section 6.3 of **Chapter 4**). To the extent that productivity growth was inhibited by the irregularity of material supplies (for eg., NCAER, 1966), *vertical integration* will have released some of these constraints, helped along by greater competition amongst suppliers.

[23] As mentioned earlier, Ahluwalia's growth rates y, n and k are slightly different from ours. However, this 'mismatch' does not interfere with appreciation of the developments in the 1980s relative to earlier years.

the notice of other commentators. Therefore it is discussed at somewhat greater length.

Behind observable effort

Here, as in **Chapter 3**, we equate observable effort with days worked per worker (or *days*). The data show that, between 1979-87, there was an increase in *days* that was *equivalent* to a switch from a five to a six day week. In fact, Saturday was an official working day even in 1979. This establishes that designated working days exceeded actual days worked in 1979, or that a significant number of days were being lost (a fifth of actual production). In the course of the 1980s, *on average* across sectors, this appears to have been more or less made up. How? And what spurred the change? In **Chapter 4**, we have hypothesized that, in the 1980s, *days* increased because (a) there was greater *uncertainty*, which led employers to favour additional days over additional workers. This is supported by the following findings. In **Chapter 4** (Section 5.1), we find evidence that *days* adjustment is significantly quicker than adjustment of the stock of employees. Furthermore, in Section 3.3 of **Chapter 3**, we record evidence that additional days are cheaper than additional workers and in **Part 1** of this chapter, we find that additional days are more productive than additional workers; (b) the 'new competition' stimulated dehoarding of inherited surpluses of labour; (c) less time was lost on account of strikes, absenteeism, machine faults and infrastructural bottlenecks; and (d) there is some evidence of an increasing tendency towards 'productivity bargains' between firms and workers (eg.,Bhattacharjee, 1987), whereby higher wages may have been negotiated in exchange for more observable effort.

Behind unobservable effort

Unobservable effort is taken to include both *diligence* and aspects of *skill* that go unrecorded. Regarding increased diligence of workers, we have three hypotheses, not unrelated to one another: (a) Higher *layoff probabilities* in the 1980s induced workers to work harder. We have noted the loss in factory jobs in **Chapter 4**. Deshpande (1992) cites evidence from Bombay of a rise in the incidence of factory closures during 1981-89. Papola (1992, p.39) reports the same for India, which confirms that the no-exit policy is not as hard and fast as made out; (b) Changing government attitudes and declining *union power* (refer

Section 6.2, **Chapter 4**) may have contributed to raising effort, though changes in the *sort* of unionism (eg., Ramaswamy 1988) are likely to have mattered more than density and militancy, the conventional measures of power. In addition, more progressive attitudes (eg., Bhattacharjee, 1987) may have made re-deployment of labour in the face of changing product market conditions easier; (c) Wages were rising rapidly. If wages elicit effort, as **Chapter 6** suggests they do, then employers may have chosen to increase wages as opposed to employment. This is especially likely if firms faced uncertainty regarding both the continuation of favourable conditions for output growth and the government's stance on labour legislation.

2.4. ESTIMATES OF TFPG BY INDUSTRY

In this section, we estimate productivity growth rates for the 18 two-digit industries that constitute aggregate manufacturing. The methodology is similar to that employed at the aggregate level, but data constraints at the industry level force some compromises, which are now discussed.

2.4.1. Method

While the coefficients on industry trends in a production function provide us with some indication of industry-specific TFPG, it is restrictive to assume that TFP evolves linearly. Moreover, the common slopes assumption, which relies upon allocative efficiency, is especially unreasonable in a less-industrialized economy. Therefore, we estimate a production function for each industry using the narrower state-time panels. This has the form:

$$\Delta y_{st} = \rho_n \Delta n_{st} + \rho_k \Delta k_{st} + \rho_d \Delta days_{st} + \theta_t + \theta_0 \qquad (25)$$

We do not restrict returns to scale and since pooling the time series for the 15 states leaves only 120 observations after first differencing, the GMM estimates are poorly determined. Therefore we adopt the procedure described in **Section 1.6**. To recapitulate briefly, we produce WG and FD-OLS estimates and use equations (17) and (16) to correct the output elasticities for ME in capital. This leaves endogeneity biases unattended. By restricting the days coefficient (β_d), we avert the problems of correcting it for both endogeneity and ME biases. This leaves the problem of a possible endogeneity bias on β_n. However, in 5 of 18 industries, employment growth was close to zero and on average in the factory sector it was -0.3% p.a. (see **Table 2, Chapter 4**). In contrast, average growth in capital stock was 7% p.a., ranging from 5 to 12% across industrial sectors. Therefore, as far as measuring TFPG is concerned, any bias in the employment coefficient is less serious than biased estimates of the productivity of capital. Armed with output elasticities corrected for measurement error in capital (henceforth, *corrected estimates*), we use the *modified Solow formula* to obtain estimates of trend growth in TFP for each industry. Given that we employ some approximations at the disaggregate level, the standard Solow estimates are presented for comparison. These are compared with Ahluwalia's numbers which, in principle, are the same.

2.4.2. Discussion Of Results

A variety of estimates

Refer **Table 2.6**[24]. There are three estimates of TFPG for each industry, corresponding to alternative restrictions on β_d, the productivity of *days*. Columns 1-3 are based on WG estimates of output elasticities, and columns 4-6, on factor shares. Where they exist, *corrected estimates* appear just below the corresponding WG estimates. In the Chemicals, Food, Paper & printing and Metal products sectors, the capital coefficients are implausibly small and our inability to correct for ME-bias in these four cases implies that the reported TFPG rates are likely to be overestimates. Corrected estimates are not computed for column 3 because it is a misspecified case that is disregarded in any case. We had noted, in studying productivity growth for aggregate manufacturing, that Solow's factor share method under-estimates TFPG. At the industry level this is even more striking, as even the ordering

[24] For each industry, the Table specifies *use-based sectors* to enable broad comparison with studies (eg. CSO 1985 and Ahluwalia 1985, 1991) that employ this 4-way disaggregation: capital goods (*kg*), intermediate goods (*int*), consumer durables (*cd*) and consumer non-durables (*cnd*).

Table 2.6
TFPG BY INDUSTRY

		Marginal products			Factor shares			Data
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry	**Use sector**	$\beta_d=1$	$\beta_d=\beta_n$	$\beta_d=0$	$\beta_d=1$	$\beta_d=\beta_n$	$\beta_d=0$	**growth in days**
Miscellaneous	*cd, cnd*	10.8 9.2	11.8	10.9	7.04	7.23	7.35	0.31 (n.s.)
Petroleum &rubber	*cnd, int*	7.0	8.6	8.6	1.53	4.83	3.91	2.38
Food products	*cnd, int*	6.3	7.4 7.1	10.4	-0.15	3.22	6.33	6.47
Cement, glass, etc	*cnd, int*	5.8 4.7	6.0	5.2	1.54	1.78	1.17	-0.37 (n.s)
Tobacco & beverages	*cnd*	5.3 3.9	6.3 5.3	7.2	-1.56	-0.80	0.88	2.44
Electrical machinery	*cd,cnd,int,kg*	4.9 4.6	4.9	5.5	2.24	2.83	2.94	0.70
Wood & furniture	*cd, int*	4.4	1.1	2.8	-0.77	-0.12	-0.10	0.67
Metal products	*cnd,int,kg*	3.2	3.0	3.8	-0.67	0.30	-0.06	0.61
Non-electrical machinery	*kg, cd*	3.3	2.4 2.3	3.5	0.90	0.49	1.35	0.45
Paper & publishing	*cnd, int*	3.5	3.9	4.0	-0.57	-0.66	-0.13	0.44
Transport equipment	*cnd, kg*	2.7 2.3	2.7 2.3	3.6	1.71	1.53	2.58	0.87
Chemical products	*cnd, int*	2.4	1.6	3.0	0.00	1.55	1.46	1.45
Textile products	*cnd (,int)*	1.7 1.4	1.8 1.7	2.2	-2.03	-1.77	-1.34	0.69
Wool & silk textiles	*cnd, int*	1.0 -0.5	1.2	1.5	-1.56	-1.09	-0.79	0.77
Cotton textiles	*cnd, int*	0.1 -1.1	1.3 0.1	1.2	-1.03	-1.54	0.56	1.59
Leather & fur	*cnd, int*	0.0	-0.3	1.0	-0.54	-1.20	0.12	0.65
Basic metals & alloys	*int*	-2.6 -3.3	-2.4 -3.1	-1.9	-3.88	-3.31	-2.89	1.01
Electricity	*int*	-3.6	-3.8	-4.0	-3.87	-2.80	-3.97	- 0.10(n.s)
Manufacturing		3.6 3.4	3.8 3.7	4.6	1.05	1.92	2.69	1.64

Notes: Figures are in percentages. In col.1-2, *corrected* estimates are in parentheses are. (n.s)=not significantly different from zero. *Industry*= 2-digit industry, *sector*= use-based sector, where cd=consumer durables, cnd=consumer non-durables, int=intermediate products, kg=capital goods.

of industries by productivity growth is not preserved (col.4-6 against col.1-3)[25]. The growth rate of *days* is in column 7. Under the assumption that β_d=1, this is the contribution of *days* to productivity growth. On average, at 1.6% p.a., it is fairly impressive. The high industry dispersion around this average is an important aspect of heterogeneous behaviour in the sample. Existing India studies that do not control for *days* give estimates of TFPG that are misleading in inter-industry comparisons. For quick reference, we have picked out from **Tables 1.7** and **2.6**, the *best industry-level estimates* (corrected if available, WG otherwise) of β_n, β_k and TFPG, under the preferred assumption, that β_d=1, and created **Table 2.8**. The best estimates for *aggregate manufacturing* are the GMM estimates from **Table 2.4**. Under the restriction, β_d=1, WG over-estimates TFPG by 1.2%-points (see **Section 2.3.2**). The ME-corrections reduce the discrepancy to 1%-point.

Studying the industry results

With reference to **Table 2.8**, 14 of the 18 two-digit industries displayed positive TFPG in the 1980s, which is quite remarkable given India's performance in the previous two decades. Subject to the inaccuracy arising from use of the standard Solow formula, **Table 2.7** shows that, except for Wood, Paper and Machinery production, every industry in India's factory sector showed negative TFPG during 1959-79. Even the three better cases had negligibly small TFPG. In fact, the 'leading sectors' in the 1980s turnaround, namely *Food, Petroleum* and *Miscellaneous*, were at the very bottom of the industry distribution in the preceding period. Our speculations on the general acceleration in productivity in the 1980s were set out in **Section 2.3.3**. We now look more closely at the *exceptions* to this trend.

The *Basic metals, Electricity* and *Textile* sectors recorded negative productivity growth in the 1980s. The fact that this is 3 of 18 sectors understates its significance. Electricity, together with Basic metals and especially the subgroup, Iron and steel, are key intermediate products in the economy. The Textile sector produces an essential consumer good, employs almost a fifth of the factory work force, and is a site of potential comparative advantage.

[25] The bases of the difference are visible in **Table 1.7.** Column 8 displays the industry factor shares, which are considerably smaller than the estimated output elasticities that replace them (columns 1-2).

Table 2.7
TFPG BY INDUSTRY
Unmodified Solow Estimates in the *Existing Literature*
Growth in days is not held constant

Industry	(1) 1959-79	(2) 1979-85	Industry	(1) 1959-79	(2) 1979-85
Miscellaneous	n.a.	n.a.	Wood & furniture**	1.8	4.4
Tobacco & beverages**	0.3	5.6	Metal products	- 0.8	-2.6
Food products	- 1.5	6.7	Non-electrical mach.	0.6	1.9
Petroleum & rubber	- 3.2	27.0	Transport equipment	1.0	1.0
Textile products	n.a.	n.a.	Cotton textiles***	1.3	0.4
Paper & publishing**	1.4	-0.7	Wool & silk textiles	n.a.	n.a.
Chemical products	- 1.3	0.4	Electricity	n.a.	n.a.
Electrical machinery	1.2	3.4	Basic metals	- 3.0	-0.5
Cement, glass etc	- 0.4	2.3	Leather & fur	- 0.4	1.0
Manufacturing	- 0.2	3.4			

Notes: Figures are in percentages. *Source:* Ahluwalia (1991). These are growth accounting estimates using the standard Solow formula. So they should compare with our estimates in column 6 of Table 2.6. (***)-The figure reported for cotton textiles is in fact the figure for the entire textile sector. **-these numbers should be understood as mere ballpark estimates. Ahluwalia's industry groups do not correspond directly to ours. The numbers with an asterisk are obtained by taking a simple average over two constituent groups. For instance, Ahluwalia reports TFPG of -3.3% in Wood and wood products and 12.1% in Furniture and fixtures. Together these two groups constitute the 2-digit industry, Wood products, to which our estimate pertains. Therefore we report her estimate as a simple average of -3.3 and 12.1.

Basic metals is known to have done poorly since the mid-60s and analyses of its performance suggest that this is on account of jerky coal supplies, tardy technological upgrading and bad planning in respect of market demands, product mix and design (see, for instance, Lall (1987) and Sengupta (1984)). While some chronic problems of the *Electricity* industry were pointed out in **Section 2.1.**, we hinted at improvements in the 1980s. The current evidence would suggest that any supply improvements had more to do with increased investment than with greater efficiency. Together, evidence of a rising plant load factor (**Section 2.1**), our finding of a zero marginal product of labour (**Section 1.6**), and employment growth of 2.6% p.a. against an average of -0.3% p.a. in this period (**Table 2, Chapter 4**), indicate that the productivity problem in Electricity is closely related to the labour policy in this industry. Unfortunately, there does not appear to be any record of the TFP performance of Electricity in the earlier period. Ahluwalia's sample excludes it because it is not part of manufacturing. Unlike Iron & steel and Electricity, which should have been

Table 2.8
Summary of Results of Parts 1 and 2
PREFERRED ESTIMATES OF TECHNOLOGY PARAMETERS AND TFPG
Dependent variable=ln(output per day), ie β_d=1

Industry	(1) β_n	(2) β_k	(3) Returns to scale	(4) TFPG
Miscellaneous	**0.61**	**0.35**	**0.96**	**9.2**
Petroleum & rubber	0.29	0.31	0.60	7.0
Food products	0.94	-0.18	0.76	6.3
Cement, glass etc	**0.96**	**0.22**	**1.18**	**4.7**
Tobacco & beverages	**0.77**	**0.12**	**0.89**	**3.9**
Electrical machinery	**0.87**	**0.19**	**1.06**	**4.6**
Wood & furniture	**1.39**	**0.08**	**1.47**	**4.4**
Metal products	1.07	0.06	1.13	3.2
Non-electrical machinery	1.05	0.16	1.11	3.3
Paper & publishing	0.77	0.05	0.82	3.5
Transport equipment	**0.95**	**0.36**	**1.31**	**2.3**
Chemical products	1.75	0.03	1.78	2.4
Textile products	**0.90**	**0.18**	**1.08**	**1.4**
Wool & silk textiles	**0.73**	**0.40**	**1.13**	**-0.5**
Cotton textiles	**0.61**	**0.36**	**0.97**	**-1.1**
Leather & fur	1.09	0.29	1.38	0.0
Basic metals & alloys	**0.64**	**0.45**	**1.09**	**-3.3**
Electricity generation	0.00	0.74	0.74	-3.6
Manufacturing	**0.69**	**0.33**	**1.02**	**2.4**

Notes: The highlighted figures are estimates corrected for measurement error in capital stock. All numbers in this Table are obtained under the restriction β_d=1. *Source*: **Tables 1.7** and **2.6**.

no worse in the 1980s than before, Textiles had a relatively hard time in the 1980s. Cotton mills had been losing market share to powerlooms in the small sector and, in 1982-83, the industry suffered an 18-month long strike (on which, see Wersch 1988, Bhattacharjee 1989). One might suspect that with shutdown, competition and the watershed of the strike, productivity would improve. While such an effect may appear with some lag, it is only extensive shedding of labour (see **Table 2, Chapter 4**) that kept total factor productivity from sinking significantly up until 1987[26].

In contrast to *all* other industries, Cotton textiles, Electricity and Basic metals experienced little or no *value added growth* in the 1980s. In spite of this, the stocks of capital and labour registered positive growth in the latter two sectors, the productivity experience of Cotton textiles being somewhat superior on account of a great loss in employment (all data are in **Table 2, Chapter 4**). Electricity and Basic metals have a relatively large fraction of their capital under public ownership[27]. It may be hypothesized that this explains their commitment to their workers *and* their ability to sustain negative productivity growth in a period of increasing competition. And it attenuates the factors identified in **Section 2.3.3** as having stimulated productivity growth, in particular, the incentive for greater effort on the part of workers. Competitiveness in the Cotton textile industry is likely to have been limited by the policy of subsidizing or adopting 'sick' mills, which continued into the 1980s (Anant *et al* (1994) is a recent analysis of industrial sickness in textile and engineering firms).

The three sectors with significantly negative *employment growth*, namely Cotton textiles, Food, and Wood products, are not clustered in the TFPG distribution. So, the connection between employment and productivity growth is not a simple one (Nickell and Kong, 1989). Notice, however, that the sectors with the most remarkable increase in *days* (ie, *Petroleum & rubber*, *Food* and *Tobacco & beverages*) are at the top of the TFPG distribution (compare columns 1 and 6, **Table 2.6**). This is consistent with the evidence in **Section 1.4** that enterprises which work more days are more efficient. The fact that this is true even after controlling for the productivity of days worked suggests that third factors were at play that led *both* TFP and *days* to rise in this period. It was argued in **Chapter 4** that we think these are infrastructural development and the competition shock, and the associated phenomena of recuperation of lost time, labour 'dehoarding', 'casualization' and subcontracting.

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[26] The strike helped the textile industry to cut employment at zero cost. In a year, the industry got rid of huge unsold stocks of cloth and excess labour that it would have taken 3-4 years to retrench and then, at an enormous cost. (Bhattacharjee, 1988).

[27] Electricity is entirely publicly owned in the period under consideration. While basic metals is a 'mixed' industry, survey information presented in Lall (1987) shows that the publicly run Indian Iron and Steel Corporation (IISCO) has been dragging down the average performance of this industry.

SUMMARY AND CONCLUSIONS

Objectives and method

While our estimates of the technology parameters serve to underpin the employment analysis in **Chapter 4**, the main objective of this chapter is to make a contribution to the literature on productivity in Indian manufacturing at a time when, arguably, productivity growth is of more interest than it has ever been. The issues taken up are primarily methodological. Careful attention is paid both to specifying and estimating production functions. The available data are a large cross-section of industry-state pairs observed over the period 1979-87. At the aggregate level, we have the luxury of sufficient data to produce fairly robust GMM estimates of the production parameters. On this sound basis, we are able to investigate restrictions on the specification, for example on the functional form, on the *days* (hours) coefficient, and on the path along which productivity evolves. Estimates of total factor productivity growth (TFPG) are based on the estimated parameters. However, once the common slopes restriction is relaxed, there are inhibiting data constraints that challenge the investigator to produce anything meaningful. Since an IV estimator proves unacceptably inefficient on the narrow state-time panels, within-groups estimates are obtained and, employing additional information from first-difference OLS estimates, these are corrected for biases to the extent possible. The best estimates of the output elasticities are used in a modified Solow formula to give estimates of industry-specific TFPG. Our estimates of TFPG are preferable to the existing estimates, all of which (i) neglect work intensity and (ii) use the traditional Solow formula, thereby assuming perfectly competitive product markets and constant returns to scale.

Aggregate results

There is no evidence of dynamics in the production function and the Cobb-Douglas approximation of the functional form is ratified by the data. Controlling for heterogeneity, measurement error and endogeneity, the marginal product of employment is *0.7* and that of capital is *0.3*. The hypothesis of constant returns to scale cannot be rejected. Given that the average share of labour over the period is 0.47, it follows from our results that, on average, workers were not paid their marginal product or are exploited in the sense of Robinson (1933, chapter 25) and Pigou (1920). This is consistent with imperfect competition in product markets and implies a price markup on marginal cost of *48%*. In contrast with existing studies for Indian manufacturing, we have controlled for variations in factor utilization to the extent possible. Apart from giving us more accurate estimates of the factor coefficients and of TFPG, this enables us to assess the opportunity cost of time lost, for example, on account of power or material shortages or as a result of industrial disputes. While the data do not reject the labour-augmenting assumption, we lean towards the view that output scales up linearly with additional days. The unrestricted estimate of the output elasticity of days worked per worker (*days*) is close to one. This implies that growth in *days* raises capital utilization and it is of particular interest in the context of Indian industry, which has a chronic affliction of excess capacity. Though it has been claimed that capacity utilization increased in the 1980s (eg., Hanson, 1989) we have seen no other direct evidence of this.

Our preferred estimate of the trend growth rate of total factor productivity in manufacturing is *2.4% p.a.*, though under alternative and plausible assumptions, it is *3.8% p.a.*. Growth in days worked contributed a *further 1.6* or *1.1% p.a.* to output growth. Given that real value added was growing, on average, at 6.3% p.a., by any count, productivity growth accounted for *more than 50%* of growth in output. This marks a substantial improvement from the preceding twenty years, when there was *no* growth in TFP. In arguing that increased effort on the part of workers (Section 2.3.3.) and, related, increased capital utilization made a significant contribution to productivity growth in the 1980s, we have adopted a more 'social' view of productivity growth than has so far occured in the Indian literature (see Weisskopf, Bowles and Gordon, 1983)[28]. The backdrop to these developments, elaborated in **Chapter**

[28] An important aspect of our viewpoint is further developed in **Chapter 6**. We have very recently come across an essay on Indian labour markets where the possibility of positive morale and nutrition effects on productivity is recognized and the complete absence of empirical verification of these possibilities bemoaned (Deshpande 1992, p.91).

4 (Section 6.4), has to do with factors like increased competition and changing industrial relations, none of which is easily quantified[29].

In a postscript to the analysis of the aggregate production function, we have retrieved the industry-state fixed efficiency effects. Exploration of region fixed effects on productivity yields some fairly interesting, if tentative, results. Persistent differences in manufacturing efficiency between states appear related to the composition of their labour forces (education, age), their structural attributes (infrastructural development, agglomeration of production, unemployment) and their industrial relations record (disputes and possibly absenteeism).

Industry results

The results obtained at the industry level are now summarized. 12 of the 18 two-digit industries exhibit constant *returns to scale*. There are increasing returns to scale in the Chemicals, Transport equipment and Leather & fur industries. Petroleum & rubber, the most rapidly expanding sector in the 1980s, shows evidence of scale inefficiencies (Table 1.9). It is recognized that the clustering around unity of the industry returns to scale parameter may in fact be the result of a happy combination of errors. There are instances (about 4 in 18) where the *capital elasticity* is implausibly small and also instances (about 9 in 18) where the *employment elasticity* seems suspiciously large (Table 2.8). The former would appear to be on account of measurement error in capital but, for these four sectors, the data reject the corrective measure proposed by Griliches and Hausman (1986). We have argued that overestimation of the employment elasticity is consistent with dehoarding in growing industries and involuntary hoarding or firing restrictions in industries with declining employment (Table 1.8)[30]. In neither case are we able to improve the estimates. If in fact

[29] For want of data, we are unable to assess the contribution of changes in educational and skill attainment of the work force.

[30] Given that employment cannot *diverge* from output, if the time dimension of the data were larger, we might get employment coefficients closer to the true parameter.

they are not the true coefficients then, in a subset of industries, our estimates of productivity growth are subject to error. However, since the growth rate of employment in the 1980s was small in most industries, any error attributable to biased employment coefficients is likely to be small. As a serious downward bias in capital occurs only in four industries, the TFPG estimates for the others are expected to be reasonably close to their true values.

Further work might exploit the ASI's *three-digit* industry data which, like our two-digit data, are disaggregated by state. This would generate sufficient degrees of freedom to enable GMM estimates of industry-level output elasticities. This is important because we have seen that, even after correction of the output elasticities for measurement error, WG tends to over-estimate TFPG. The process of liberalization, which was gradual and tentative during the 1980s, received a sharp boost in 1991 with the introduction of the *new economic policy* under IMF conditionalities. It would be interesting to investigate whether the increase in TFPG observed in 1979-87 continued, or perhaps accelerated, after 1991. As the ASI statistics appear with a lag of four years, this will be possible a few years from now. Further work must also address the question of the sustainability of productivity growth. Improvements in efficiency arising, for example, from liberalized access to technology imports may continue. However, between a third and two-thirds of productivity growth was the outcome of longer hours (*days*) worked in Indian factories. The natural ceiling on hours implies that this contribution is not sustainable. To this extent, the celebration of the turnaround and, associated, of the new policies, may prove to have been somewhat overdone.

CHAPTER 6

A DIRECT INVESTIGATION OF THE EFFICIENCY WAGE HYPOTHESIS

1. INTRODUCTION

The analysis here shares spirit with **Chapter 3** and takes body from **Chapter 5**. Our investigation of wage determination in **Chapter 3** (Part 3) established that productivity and other industry-specific variables have a significant impact on industry earnings. This is consistent with both rent-sharing and efficiency wage theories and the estimated earnings equations have no power to distinguish the two, leaving us short of evidence that efficiency wages are paid by Indian manufacturers[1] Preliminary evidence in this direction was garnered by studying the industry wage structure in Parts 2 and 4 of **Chapter 3**. It is the purpose of the present exercise to take this further by directly investigating the basic efficiency wage hypothesis. While in a bargaining framework it is clear that the firm would choose a lower wage in the absence of insider (or union) power, in efficiency wage models firms set the wage at an optimizing level. In the latter case, it must be that the additional revenue reaped by the payment of wages in excess of the supply price of labour offsets the additional cost incurred. This simple fact affords a direct test of the efficiency wage hypothesis. In this chapter, we conduct such a test by estimating a production function that incorporates the arguments in the workers' effort function. In **Section 2**, we consider the relevance of different versions of the efficiency wage model to our domain in India. **Section 3** models effort effects on productivity under alternative assumptions and **Section 4** describes existing work on the subject, delineating our contribution. In **Section 5**, we develop an empirical specification, and estimates of this are discussed in **Section 6**. In **Section 7**, we summarize our inferences.

[1] Were union power and hysteresis terms significant in the earnings equations, we could claim support for the bargaining or rent sharing regime. Having failed to find any such econometric evidence, the view that there exists *wage* bargaining rests delicately on common observation buttressed by the evidence in a small and unrepresentative sample of employment contracts gathered from personnel managers in India.

2. CONTEXTUALIZING SOME EFFICIENCY WAGE MODELS

The idea that an increase in the relative wage induces an increase in productivity is consistent with more than one mechanism. We shall briefly discuss some of these, and their possible relevance in the Indian factory setting. Real insight into the relative importance of these mechanisms can only stem from direct knowledge of workers' alternatives and of hiring and firing procedures as actually implemented. As this is something that, so far, we do not have enough of, the following should be seen as no more than broad guiding principles. Also, it is recognized that effort may depend upon perquisites such as housing provisions[2], which are not measured by the wage. Our purpose is to investigate whether the wage counts nonetheless. In the *shirking* model (Shapiro and Stiglitz, 1984), effort depends on the relative wage on the assumption that there is occasional monitoring that picks out shirkers and penalizes them with job loss. This sort of motivation argument is more plausible for casual than for regular workers, as there are restrictions against the firing of regular workers. As casual workers constitute only a small fraction of India's factory work force (4.6% in 1980 and 10% in 1987; CSO), this version of the model may not pull much weight. It is further undermined by a case study of a cotton textile mill in Ahmedabad, where a 'controlled experiment' showed that persuasion by the supervisor led to greater efficiency but threat of suspension resulted in a deterioration in efficiency (Murphy 1953:211-212, cited in Papola, 1992, p.33). The *turnover* model (eg., Salop, 1979) poses a relatively high wage as a deterrent to quits, and the *adverse selection* model (Weiss, 1980) proposes that high wages will serve to select the higher quality workers from a large pool of candidates. A combination of the turnover and selection hypotheses may, as we shall now see, be especially relevant to less industrialized economies (LIEs).

Urbanization has increased, 26% of the population being in urban areas in 1991 as against 17.3% in 1941 (Papola, 1992), but two-thirds of the Indian population still resides in rural

[2] The Tata Iron and Steel Company has often been cited as a model private employer. It created the city of Jamshedpur from a small village in Bihar in the early 20th century, providing housing, schools and other amenities to workers. Morris (1960) reports that, although virtually all of its workforce was migrant, absenteeism and quits were insignificant.

areas. Therefore, rural-urban migration continues to supply a large part of the urban workforce. In this sense, the formation of an industrial labour force is still in progress. At the same time, the phenomenon of considerable return (urban to rural) migration suggests that it is possible that employers may need to create incentives to retain good workers[3]. Mazumdar (1984) captures this idea in the argument that the *supply price* of *permanent migrants* exceeds that of temporary or circulating migrants. Permanent migrants typically bring their families with them. This usually means a loss of farm income and since women and children are less easily absorbed into the urban as compared to the rural economy, a fall in the earner-dependent ratio. While temporary and single migrants tend to find 'free' accommodation in the city[4], permanent migrants incur substantial housing costs. The

Table 1
Average Family Size in Bombay

Sector	Migrant	Non-migrant	All
Factory	3.30	5.59	3.99
Casual	2.34	4.49	2.88
Small scale	2.30	5.59	2.97

Notes: These data are based on a survey of workers in Bombay in 1972/73. *Source*: Mazumdar (1984)

demand price of permanent migrants is relatively high in occupations and industries where a stable work force matters relatively more to productivity. Though Mazumdar poses his argument as a competitive explanation, it may be construed as an efficiency wage explanation of factory wage-setting. Like other efficiency wage models, it also explains dualism in the labour market (Akerlof, 1984): firms that are willing to offer wage premia

[3] Out-migration from Bombay in the 1950s offset roughly half of in-migration. As a fraction of the stock of migrants in 1961, the outmigration rate was 20% and the highest rate of outmigration was among 30-35 year olds (Census data reported in Zachariah, 1968). Studying pre-Independence India, Gadgil (1942:127-130) has observed that, as a result of surplus labour resources in the countryside, employers did not treat workers well and therefore workers either did not move out of their village or, if they did, were quick to return.

[4] In the factory sector, for example, 14% of single migrants slept at their place of work, 38% lived with friends and relatives without any payment and only 36% lived in rented houses (Mazumdar, 1984).

to recruit and retain migrants elect themselves into the primary sector. Temporary migrants are absorbed as secondary sector workers. The data in **Table 1** are consistent with the idea that factories employ a greater share of permanent as opposed to temporary migrants.

The argument that permanent migrants claim a wage premium on account of their stability implies that stability is scarce. Since Mazumdar's hypothesis strikes us as rather plausible, we now attempt to reconcile it with the notion of a labour surplus in the cities. In other words, if there are enough (stable) natives looking for employment, why do factory managers have to woo migrants into permanency? They don't, according to Papola (1992, p.21), whose argument is based simply on the *numbers* of urban-dwellers available for work. However, there is some evidence that factory employers hire (permanent) migrants in preference to local workers. Although Mazumdar does not address this question, his Bombay survey demonstrates that most factory jobs go to migrants (1984; Tables 5 and 10) and based on a survey of Delhi workers, Banerjee (1983) provides supporting evidence. But why might underemployed and unemployed urban 'incumbents' be poor competitors? One possibility is that, like the long-term unemployed in European nations (see Nickell, 1987), they are discouraged or de-skilled and so have low search intensities. Another is that they are known by employers to have lower ability than migrants. Migrants may have to strive hard in the new environment where buffers (family, land) are scarce and by a process of self-selection, they tend to be a highly motivated group. A less traditional argument is that the relative success of migrants in the formal labour market reflects the well-documented tendency for Indian employers to hire relatives and friends of employees (eg., Lambert 1963, Papola and Subrahmanian 1975, Deshpande 1979 and Harris *et al* 1990. In all of these studies, 60-70% of recruitment operated by community 'contacts'.)[5]. Given that a good proportion of factory employees are migrants and that community ties are strong, fresh migrants will have both an informational advantage and a priveleged candidature if they are well-connected. In sum, there exist reasons why the Indian factory employer may volunteer

[5] These informal mechanisms are not uncommon in LIEs. Caldwell (1969) adduces evidence of similar behaviour in Ghana, where the majority of rural migrants said that they could rely upon relatives and their village folk for 'accommodation, food *and job placement*'.

an uncompetitively high wage *despite* the existence of surplus labour.

The *sociological* variant of the efficiency wage hypothesis (Akerlof, 1982) appears to be more transparently relevant to the Indian setting than any of the others. The idea is that an increase in the relative wage translates into higher effort as workers reciprocate the employer's 'gift'. Loyalties are very strong in India and when workers are happy it is not uncommon that they look upon their employer as their benefactor. Thus a high relative wage may induce high morale, given that notions of fairness are relative (Akerlof cites sociological evidence)[6]. If instead of comparing with an external reference group, workers compare their living standards with their employers', the ratio of wages to profits may be a better fairness variable than the relative wage, but this idea is not pursued here. The *union threat* model (Dickens, 1986) appears to us to be closely related to the Akerlof model. A wage premium placates workers and discourages them from unionizing, or more generally, from perpetrating work stoppages or being inflexible about their job description. The productivity effects of 'amicable industrial relations' can be quite significant.

Finally, a version of the original efficiency wage model (Leibenstein, 1957) may have some relevance. Here it is not the relative wage but the absolute consumption wage that influences effort. Leibenstein proposed that where *living standards* border on subsistence, any increase in the real wage would immediately result in higher effort for simple biological reasons. Supposing that each factory worker has three dependents, his or her income is at the per capita level. This covers subsistence but since India is a low income country, it is small enough that factory workers, on average, spend 80% of their income on food (Chatterji, 1989). Therefore, small increments to income are likely to be associated with visible increases in well-being. A higher wage income may make the worker more productive for given food expenditure. For example, the worker may be able to live closer to the factory, avoiding a long commute that would otherwise leave him or her quite tired at the start of

[6] Note that while the relative wage reflects alternative opportunities in the shirking model, in the absence of any threat of layoff it reflects fairness. In the first case efficiency is induced by fear and in the second, by positive morale effects.

the working day. Myers (1958:49-50) cites company officials and supervisors in Indian industry, in 1954, as saying that the Indian worker would be as efficient as any, were it not for poor nutrition and bad living conditions at home and unsympathetic supervisors at work. However, since 1954, the living standards of factory workers have improved. Therefore, whether the real consumption wage had any impact on productivity in the 1980s merits investigation.

3. MODELLING EFFORT EFFECTS

3.1. Effort directly affects productivity

As in **Chapter 3** (Section 3.1), we specify the production function to include observable (D) and unobservable effort (E):

$$Y_{jt} = \exp(\tau_t+\lambda_i t)\ A_j\ [E_{jt}(.)]^{\gamma}\ D_{jt}^{\delta}\ N_{jt}^{\alpha}\ K_{jt}^{\beta}\ \nu_{jt} \tag{1}$$

where subscripts j, i and t refer to firm, industry and time, Y refers to value added, N is employment, K is capital stock, D is days worked per worker (or *days*), E is unobserved effort, A is an index of time-invariant firm-specific productivity, λ is industry-specific productivity growth, τ are time-specific effects that are common across firms, and ν is an i.i.d. productivity shock that is assumed to be uncorrelated with changes in A, N, D and K. Notice that the marginal productivity of effort is allowed to differ from that of workers ($\gamma \neq \alpha$). Under the efficiency wage hypothesis, effort can be substituted out by its determinants, with the advantage that these are observable. In view of the preceding discussion of the theory, effort is modelled as a function of both the relative wage and the absolute consumption wage:

$$E = E(W_{jt}/P^{c}_{t},\ W_{jt}/W^{a}_{t}) \tag{2}$$

where P^c=a cost of living index, W=own wage, W^a=alternative wage and both W and W^a are expressed in nominal terms. Log-linearizing and substituting (2) in (1) gives:

$$y_{jt} = \tau_t + \lambda_i t + a_j + \gamma[\kappa_1\log(W_{jt}/P^{c}_{t}) + \kappa_2\log(W_{jt}/W^{a}_{t})] + \delta days_{jt} + \alpha n_{jt} + \beta k_{jt} + \varepsilon_{jt} \tag{3}$$

where lowercase letters denote logs, *days*=logD and ε=logν. If efficiency effects flow from the payment of relatively or absolutely high wages then the wage terms in (3) will be significant. However the efficiency wage hypothesis can make a finer prediction than this. A defining condition of the optimal efficiency wage is that, *ceteris paribus*, an increase of x% in the wage should yield the same increase in output as an x% increase in the measurable labour input. In other words, $\gamma(\kappa_1+\kappa_2)=\alpha$ or, if effort depends only on relative wages, then $\gamma\kappa_2=\alpha$. If wage bargaining coexists with efficiency wage considerations, then the wage does not quite pay for itself and $\gamma(\kappa_1+\kappa_2)<\alpha$, or $\gamma\kappa_2<\alpha$. These conditions are demonstrated in **Appendix 6.1**. We do not expect $\alpha=\delta$ unless additional *days* are as productive as additional workers. Since additional *days* are expected to increase capital utilization while additional workers on a given day may be knocking elbows over the same capital, in general we expect that $\delta \geq \alpha$ (refer **Chapter 5**).

3.2. Effort affects returns to labour

An alternative hypothesis that is consistent with efficiency wage models is that, *ceteris paribus*, effort affects output by raising the marginal returns to labour. In other words,

$$Y_{jt} = \exp(\tau_t+\lambda_i t)\ A_j\ D_{jt}^{\delta}\ N_{jt}^{\alpha}\ K_{jt}^{\beta}\ \nu_{jt}, \text{ where } \alpha = \alpha_0 + \alpha_1 \log E(.) \tag{4}$$

Then using (2) gives the alternative production function:

$$y = \tau_t + \lambda_i t + a_j + \alpha_1[\kappa_1 \log(W_{jt}/P^c_t)n_{jt} + \kappa_2 \log(W_{jt}/W^a_t)n_{jt}] + \delta days_{jt} + \alpha_0 n_{jt} + \beta k_{jt} + \varepsilon_{jt} \tag{5}$$

where significance of the nonlinear terms offers support for the efficiency wage hypothesis.

4. EXISTING WORK

Although efficiency wage ideas have been around for a long time (Dunlop, 1988), empirical studies designed to investigate their validity in particular contexts are still rather scarce. There are two ways in which one may adduce evidence in support of the efficiency wage hypothesis. The first is to draw inferences from the properties of the industry wage structure, as was done in Part 2 of **Chapter 3**. The second is to directly investigate the hypothesis by looking for efficiency wage effects on productivity, and this is what is done here. To my knowledge, there are just four other studies that have gone along this route, all of which are fairly recent. Both Wadhwani and Wall (1991) and Nickell and Nicolitsas (1994) estimate a production function on a panel of British manufacturing firms in the 1980s. They find that both relative wages and industry/aggregate unemployment rates have a significant positive effect on productivity. Moreover, Wadhwani and Wall establish that the relative wage effect is weaker when unemployment is higher. Similar evidence for US industry emerges from Levine (1992) and Straka (1989), who consider only relative wage effects. Straka also shows that efficiency wage effects are weaker in firms that have strong unions.

Our investigation shares with the British studies the virtue of using an instrumental variables (IV) procedure that elimates feedback from productivity to wages. The US studies are subject to the criticism that what appears as an efficiency wage effect may in fact be a rent-sharing effect running from productivity to wages. Wadhwani and Wall (1991) and Levine (1992) investigate whether efficiency wages pay for themselves but their formalization of this question is rather *ad hoc*. In **Appendix 6.1**, we formally establish the relevant restriction in the context of a very general production function that encompasses those specified in the cited studies. While we are forced by data limitations to (virtually) neglect investigation of unemployment effects, the effort function that we specify has the unique feature of allowing the absolute level of the consumption wage to matter in addition to the relative wage. Also, as far as we know, this is the first direct test of the efficiency wage hypothesis in a developing country. In a comment on the analysis of productivity growth in Ahluwalia (1991) (see **Chapter 5**), Deshpande (1992, p.91) admits the possibility that rising consumption wages improved nutrition and morale. But, he says, 'these logical possibilities are rarely entertained for want of attempts at empirical verification'.

5. AN EMPIRICAL SPECIFICATION

The data are a panel of 240 industry-state observations for 1979-87 (see **Data Appendix**). The theoretical production function was developed for firms indexed j. We now replace j

with the subscript '*is*', denoting industry-state. Then eq. (3) can be cast as:

$$y_{ist} = \tau_t + \lambda_i t + a_{is} + \gamma[\kappa_1 \log(W_{ist}/P^c_{st}) + \kappa_2 \log(W_{ist}/W_{st})] + \delta days_{ist} + \alpha n_{ist} + \alpha k_{ist} + \varepsilon_{ist} \quad (6)$$

Equation (6) and the analogous form of eq. (5) are now prepared for an empirical investigation. The basic efficiency wage variable is the relative wage (W/W^a), the alternative to the industry-state factory wage (W_{ist}) being specified as the corresponding state average ($W^a = W_{st}$). In the wage equation estimated in **Chapter 3**, W_{st} behaved as a very reasonable proxy for W^a, acquiring a substantial coefficient of about 0.3. However, if the reference group (or relevant alternatives) lie(s) outside the factory sector, then wages in the rural and urban informal sectors might better represent W^a. Lacking appropriate data on these wages, it is hoped that the average factory wage (W_{st}) will proxy movements in these variables at the same time as standing on its own. The real consumption wage (W/P^c) is obtained by deflating the nominal day wage rate (W_{ist}) by a *state-specific* index of the cost of living of industrial workers (P^c_{st}). The first lag of each of these terms is also included in the empirical specification to permit delayed effects. To investigate the alternative hypothesis that output depends on the wage terms, not directly, but through the labour coefficient, each of these terms is interacted with n to give the terms $n\log[W/P^c]$ and $n\log[W/W^a]$. Other variables are described in Section 1.3.2, **Chapter 5** and the **Data Appendix**.

Year effects common across industry-state units are captured by time dummies (τ_t). This is convenient as τ_t will include variables that we do not have measures for such as changes in the competitiveness of the entire manufacturing sector. Unobserved effort is substituted out by its determinants, the wage terms. Effort may, in addition, be influenced by unemployment, which is expected to be picked up by a combination of time dummies and industry-state fixed effects. Any unobserved time-invariant effects on efficiency levels (a_{is}) are eliminated by first-differencing. In the first-differenced equation, industry-specific productivity trends ($\lambda_i t$) enter as industry dummies. Productivity shocks in the error (ε_{ist}) will be correlated with factor utilization and with changes in the skill composition of employment. Therefore both factors (n_{ist}, k_{ist}) are instrumented. In **Chapter 3**, we have established that productivity has a positive impact on wages. In view of the possibility of reverse causality, the efficiency wage terms (W_{ist}/P^c_{st}, W_{ist}/W_{st}) are also treated as endogenous. The equation is estimated by the Generalized Method of Moments (GMM) (see Section 3.2.2, **Chapter 3**).

6. RESULTS: THE PRODUCTIVITY EFFECTS OF HIGH WAGES

Results are in **Tables 2-4**. The GMM estimates are obtained using the second and longer lags of all included variables as instruments (see Notes to Tables), and the diagnostics are satisfactory. We report first-step GMM estimates. We find that the second-step estimates are always better determined and often have larger coefficients on most variables, but Monte Carlo simulations conducted by Arellano and Bond (1991) indicate that these can be spuriously good[7]. To assess the importance of IV, we also present WG estimates of the main equations.

To avoid digressing later, it is worth reporting right away that, using the regional panel (**Chapter 2**:14 states, 4 years), we estimated a state-level production function with the unemployment rate included as an explanatory variable but it had no discernible effect. However, in Table 1.6 of **Chapter 5**, we found a positive correlation (0.38) between the unemployment rate and region fixed effects on productivity, significant at 12%. Further work in this area is needed before any conclusions can be drawn.

6.1. The Relative Wage

Column 1 of **Table 2** reports the basic production function, borrowed from **Table 1.2** (col.6) in **Chapter 5**. As its parameters were discussed in the preceding chapter, attention is now focused on the efficiency wage terms. Column 2 shows the case where effort depends on the *relative wage* (w_{ist}-w_{st}). The relative wage has a statistically significant coefficient of nearly 0.7, indicating that efficiency wages are paid. As this is only marginally different

[7] Since Wadhwani and Wall (1991) report the second-step GMM estimates, interpretation of their results should take this into account.

from the employment coefficient, the hypothesis that efficiency wages pay for themselves

Table 2
Efficiency Wage Effects
THE RELATIVE WAGE
Dependent Variable=y_{ist}

	basic production function	*include relative wage*	*drop year dums. in (2)*	*drop days in (2)*	*no IV in (2)*	*allow $\alpha_i n$ in (5)*	*add industry trends in (2)*
Estimator	GMM	GMM	GMM	GMM	OLS-OD	OLS-OD	GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.07 (2.3)	0.07 (2.5)	0.02 (1.7)	0.04 (1.7)	-0.18 (8.3)	-0.15 (5.4)	0.10 (2.9)
employment	0.69 (3.4)	0.66 (3.2)	0.78 (4.3)	0.53 (2.9)	0.63 (8.2)	1.03** (4.7)	0.53 (2.9)
capital	0.33 (2.5)	0.33 (2.8)	0.31 (2.7)	0.27 (2.4)	0.23 (5.1)	0.21 (5.3)	0.29 (2.3)
days/worker	0.93 (2.4)	0.94 (2.5)	1.04 (3.1)		0.47 (4.0)	0.45 (3.7)	0.46 (1.3)
rel.wage		0.68 (2.6)	0.70 (2.5)	0.75 (2.3)	0.24 (3.1)	0.21 (2.8)	0.74 (2.4)
Wald [RHS]	39.5/3	61.9/4	75.0/4	38.8/3	124.4/4	788/21	267.4/21
Wald [year dummies]	17.7/7 (0.02)	16.3/7 (0.02)	n.a.	22.3/7 (0.0)	44.1/7 (0.0)	38.4/7 (0.0)	21/7 (0.0)
Wald [$\lambda_i t$]	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	36.4/17
σ^2	0.121	0.124	0.125	0.123	0.130	0.122	0.121
ser corr(1)	-6.8	-6.5	-6.5	-6.0	-6.4	-6.7	-6.2
ser corr(2)	0.70 (0.48)	0.76 (0.45)	0.91 (0.36)	-0.28(0.78)	0.12(0.91)	0.07 (0.94)	0.16(0.88)
Sargan χ^2	56.5/57 (0.49)	67/71 (0.61)	62.6/71 (0.75)	56.8/57 (0.48)	n.a.	n.a.	72.7/71 (0.42)

Notes: rel. wage=relative wage; see **Data Appendix** on notation. Total observations=1818, N=262, T=7 (1981-87), unbalanced panel. *Instruments* are n(2,4), k(2,4), days(2,4), [w-p](2,4) and where appropriate, [w-p^c](2,4), [w-w$_{st}$](2,4), τ_t and $\lambda_i t$, where x(a,b) is used to denote $x_{t-a},..,x_{t-b}$. No instruments in col. 5 and 6. α_i are industry-specific employment coefficients. **: The reported employment coefficient is that for the *base* industry, Chemical Products. 6 of the remaining 17 industries have significantly smaller coefficients: Electricity, Electrical Machinery, Food Products, Petroleum & Rubber, Tobacco & Beverages and Textile Products. No industry has a significantly larger coefficient than Chemicals.

cannot be rejected. The time dummies are jointly highly significant and there is no remarkable change in the other production function parameters. Column (3) reports an equation from which year dummies have been dropped and column (4) reports the same when *days* is dropped. In both cases, the coefficient on the relative wage coefficient is somewhat bigger. These experiments demonstrate the consequences of neglecting to control for aggregate productivity effects and observed effort respectively.

The conclusion that increases in the relative wage stimulate effort may be regarded as subject to at least two alternative interpretations. One is that what we observe is reverse causality, or the positive effect of productivity on wages, observed in the wage equation estimated in **Chapter 3**[8]. In fact, since the relative wage is instrumented, there is little scope for a reverse causality argument. The Sargan test statistic confirms that the instruments are not significantly correlated with the residual. Nevertheless, for comparison, column (5) reports WG estimates corresponding to the GMM estimates in col. (2). The relative wage coefficient is expected to be larger under WG on account of positive feedback. In fact it is smaller, the difference being just short of two standard errors. This suggests that, in this sample, productivity shocks cause opposing movements in productivity and wages[9] and that this dominates the reverse or rent-sharing effect. However, what is pertinent is that the comparison establishes that the coefficient on the relative wage is not corrupted by its endogeneity. The second issue that we must address is the possibility that a positive wage-productivity correlation is the consequence of inadequate controls for skill shifts. Different industries are associated with different technologies that imply different skill compositions and these differences are expected to be captured by the fixed effects. However if the proportions in different skill groups change over time, then fixed effects are not adequate and we may find that industries that employ relatively well-skilled workers will exhibit relatively high wages and relatively high productivity in the absence of any efficiency wage mechanism. More precisely, if industry technology differences imply different employment coefficients (α_i), then the common slope restriction ($\alpha_i=\alpha$) forces the terms $(\alpha_i-\alpha)n_{ist}$ into the error. As these terms are, very likely, positively correlated with the relative wage, $(w_{ist}-w_{st})$, its coefficient will be biased upward. To take account of this, we re-estimate the

[8] One standard route around this is to replace the current with the lagged relative wage. This is done and the lagged term turns out to be positive but insignificant. So this route does not help.

[9] In principle, this could be, for example, on account of a change in union power.

production function, allowing industry-specific employment coefficients (α_i). If the efficiency wage term is not significantly smaller, then the argument that it reflects poorly controlled skill-differences is weakened. Comparison of the equation in column 6 with its common-slope analogue in column 5 demonstrates that this is the case. Notice that we have conducted the last experiment using WG. This is done because there are 18 potentially endogenous employment terms, which would make for too many instruments under GMM. As we are comparing like with like across (5) and (6), the fact that the WG estimates carry a downward bias (see **Chapter 3**, Section 3.2.2) is not relevant. An alternative way of controlling for time-varying skill differences between industries is to include industry-specific trends in the equation. Results of such an experiment are in column (7). Once again, the relative wage is no smaller.

6.2. Earnings, Adaptation and Consumption Wages

In **Table 3**, we consider alternative specifications of the effort function. In column 1, the relative wage (w_{ist}-w_{st}) is replaced with relative earnings (ω_{ist}-ω_{st}). If workers derive no utility from days lost, for example on account of a power cut or a lockout, then this may be the relevant variable. While relative earnings claims a larger coefficient than the relative wage, the days effect is considerably smaller[10]. The relative earnings coefficient is not significantly different from the employment coefficient which indicates, again, that increments to workers' salaries inspire sufficient effort to justify them. Thus far, we have seen that workers care about how their income compares with that of a reference group. Are they also concerned with how it compares with their past real income? To investigate this, in column (2) the *change* in the real consumption wage is incorporated in the production function. We find no evidence in favour of adaptation. However, there is compelling

[10] This is, very likely, a reflection of the positive correlation between *earnings* and *days*. Note that although *days* figures independently in both, this does not make the relative wage and relative earnings specifications equivalent. Denote y=output, d=*days*, ω=annual earnings and let superscript 'a' denote alternatives. Then the wage, w=ω-d. It follows that the relative wage is $[w-w^a]=[\omega-d]-[\omega^a-d^a]$ and relative earnings=$(\omega-\omega^a)$. Although *days* (d) appears in both equations, d^a figures in the relative wage equation and not in the relative earnings equation.

evidence of a positive effort effect from the *level* of the consumption wage[11] (column 3),

Table 3
Efficiency Wage Effects
EARNINGS, ADAPTATION AND CONSUMPTION WAGES
Dependent Variable=y_{ist}

	relative earnings	*real wage growth*	*consumer wage*	*drop year dums in (3)*	*drop days in (3)*	*add industry trends to (3)*	*no IV in (3)*
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	OD-OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
constant	0.05 (1.9)	0.03 (1.1)	0.08 (2.8)	0.005(0.41)	0.034(1.4)	0.09 (3.2)	-0.15(6.8)
employment	0.72 (3.6)	0.63 (3.4)	0.71 (3.5)	0.80 (4.0)	0.55 (2.8)	0.47 (2.1)	0.61 (8.7)
capital	0.34 (2.8)	0.35 (2.8)	0.30 (2.1)	0.37 (2.6)	0.37 (2.7)	0.25 (1.4)	0.22 (5.8)
days	0.56 (1.5)	0.70 (1.9)	1.00 (3.0)	0.78 (2.6)		0.40 (1.0)	0.45 (4.0)
rel. earnings	0.81 (2.8)						
cons. wage			0.79 (2.6)	0.44 (1.5)	0.57 (1.8)	0.75 (2.5)	0.26 (3.2)
Δcons. wage		0.03 (0.4)					
Wald [RHS]	67.7/4	43.8/4	65.4/4	67.2/4	50.3/3	245.7/21	239.7/4
Wald [year dummies]	17.7/7 (0.0)	9.1/6 (0.17)	18.9/7 (0.0)	n.a.	16.4/7 (0.02)	30/7 (0.0)	55.8/7 (0.0)
σ^2	0.121	0.127	0.131	0.124	0.124	0.123	0.126
serial corr(1)	-7.0	-7.4	-7.0	-6.9	-7.3	-7.3	-7.2
serial corr(2)	0.53 (0.59)	-0.37(0.71)	1.4 (0.17)	0.91 (0.37)	-0.18(0.86)	0.46 (0.64)	0.39 (0.70)
Sargan χ^2	81.6/74 (0.26)	69.3/65 (0.34)	59.2/59 (0.47)	62.1/57 (0.30)	60/58 (0.41)	61/63 (0.55)	n.a.

Notes: See notes to **Table 2**. In all cases, NT=1818, N=262, T=7, except in column (2) where T=6 and NT=1556. *Instruments* are as in Table 2, with $[w-p^c](2,4)$ replacing $[w-w_{st}]$ in col. 2-6. No instruments in col.7.

and once again there is support for the idea that efficiency wages pay their way. This may be interpreted as support for the modified nutrition efficiency wage argument (**Section 2**). Alternatively, it may merely represent the relative wage effect identified earlier, with the alternative or comparison wage being captured by a combination of time dummies and fixed effects. The specification of the comparison wageas the state average of the factory wage may be mistaken, for example, because the relevant alternative is the rural wage (as is

[11] Again earnings and not wages may be relevant. But, now, having the real wage in the equation is equivalent to having real earnings since *days* is being held constant.

plausible under the recruitment-retention story discussed in **Section 2**). Under such circumstances, this equation is more general than that in **Table 2**.

To investigate whether unobserved effort responds positively to absolute consumption standards, *given* relative pay, we estimated an equation that includes both. The consumption wage coefficient is larger and significant, but the relative wage is no longer significant. Two interpretations are possible. One is that while both effects may matter, the equation does not have the power to identify independent effects from the two variables because they are nearly collinear. The other is that, of the alternatives discussed in **Section 2**, the modified-'nutrition' model of efficiency wages is the most pertinent to the Indian setting.

Columns 4-7 (**Table 3**) repeat the experiments performed in **Table 2,** replacing the relative with the absolute consumption wage. Columns 4 and 5 show that, contrary to the analagous results in **Table 2**, failure to control for common macroeconomic effects on productivity and for variations in work intensity results in an *underestimate* of the consumption wage effect. This affords some support for the idea that the consumption wage effect is indistinguishable from a relative wage effect, with the year dummies helping to control for the reference wage. Comparison of columns 6 and 3 reveals that employing more comprehensive controls for skill variation does not lower the wage effect on productivity. Finally, in column 7 we report the WG equivalent of col.3. This has a similar interpretation to the analagous equation in col.5 of **Table 2**.

6.3. Allowing Effort to Affect the Output Elasticity of Employment

We now turn our attention to estimates of the production function that embodies the hypothesis that wage incentives provided by the firm augment returns to labour (equation 5, Sec. 3). The basic production function is in column 1 of Table 2 for reference. Refer to **Table 4**. The first column incorporates the interaction of employment with the relative wage and column (2) includes a similar term in the absolute consumption wage. In each case the nonlinear efficiency wage term is well-determined and positive. For comparison, WG estimates of the two equations are also reported. They behave similarly to the WG estimates of the equations that allow direct efficiency effects. Note that as the mean of logged employment is 9.40, the wage elasticity of output[12] implied by equations (3) and (5) is very similar.

Table 4
Efficiency Wage Effects
RETURNS TO LABOUR DEPEND ON EFFORT
Dependent Variable=y_{ist}

	relative wage	*consumption wage*	*(1) with no IV*	*(2) with no IV*
Estimator	GMM	GMM	OD-OLS	OD-OLS
	(1)	(2)	(3)	(4)
constant	0.07 (2.5)	0.08 (2.8)	-0.16 (6.1)	-0.15 (7.0)
employment	0.55 (2.8)	0.90 (4.3)	0.64 (8.1)	0.67 (8.9)
capital	0.31 (2.5)	0.27 (2.3)	0.23 (5.1)	0.22 (5.8)
days	0.87 (2.3)	0.94 (2.7)	0.47 (4.0)	0.45 (4.0)
$n(w-w_{st})$	0.074 (2.3)		0.023 (2.7)	
$n(w-p^c_{st})$		0.069 (2.3)		0.023 (2.8)
Wald [RHS]	41.4/4 (0.0)	74.5/4 (0.0)	121.2/4 (0.0)	231.2/4 (0.0)
Wald [year dummies]	17.4/7 (0.0)	20.0/7 (0.0)	44.6/7 (0.0)	57.7/7 (0.0)
σ^2	0.136	0.126	0.138	0.127
serial correlation(1)	-6.5	-7.0	-6.4	-7.2
serial correlation(2)	0.62 (0.53)	1.2 (0.23)	0.06 (0.96)	0.30 (0.76)
Sargan χ^2	61.6/71 (0.78)	70/71 (0.74)	n.a.	n.a.

Notes: See notes to **Table 2**. n is employment, $(w-w_{st})$ is the relative wage and $(w-p^c_{st})$ is the absolute consumption wage. *Instruments* in col. 1 and 2 are n(2,4), k(2,4), days(2,4), [w-p](2,4), τ_t and $[n][w-w_{st}](2,4)$ or $[n][w-p^c](2,4)$ as the case may be.

[12] In column 1 of **Table 4**, for example, $\partial y/\partial w=0.074n$, where w is the relative wage and all variables are in logs.

7. CONCLUSIONS

The evidence is that efficiency wages are paid in Indian factories. In independent specifications, effort appears to be stimulated by increases in relative wages and absolute consumption wages. However, in a competition between the two, the absolute consumption wage is the winner. Thus, there is some support not only for the fairness and the selection-turnover models, but also for our modified 'nutrition model'. Increments in either of the relative and absolute wage have sizeable effects on productivity, the elasticities lying in the range 0.7-0.8. In view of our investigations it seems unlikely that this simply reflects unobserved skill variation or the positive effect of productivity on wages. The data cannot distinguish whether effort affects productivity directly or through the marginal return to employment, there being significant effects under both specifications. There is some support for the notion that the comparison or alternative income is that of other factory workers. In general, there is a days effect [observed effort] that is independent of the wage effect [unobserved effort] on productivity. There is no evidence of adaptation, that is that the level of current relative to past wages stimulates effort. Of particular interest, the evidence is not inconsistent with the condition that efficiency wages pay for themselves. This undermines the importance of wage bargaining in Indian factories (see **Appendix 6.1**).

It should be reiterated that our evidence of efficiency wage payments stems from the restricted domain of the factory sector, a significant part of the 'urban formal sector', where most of the regular jobs are. Wages are considerably lower in the informal sector. For instance, in a large sample of urban males surveyed in 1987, regular workers earned Rs. 42/day and casual workers earned Rs. 17/day (Sarvekshana 1990, Tables 79 and 81U). Hence, while it is not evident that the market for casual workers clears, it appears to be a 'secondary' labour market. Efficiency wage models provide a rationalization of the primary-secondary labour market dualism (Doeringer and Piore 1971, Akerlof 1984) that is deeply entrenched in most less industrialized economies (eg., Kanbur and McIntosh, 1991). The basic idea is that industries in which effort or stability matters, at least in some occupations, tend to select themselves into the primary sector labour market.

Appendix 6.1

THE MODIFIED SOLOW CONDITION

The Solow condition is that the effort-wage elasticity is unity. Here, we modify it to take into account the possibilities that (i) effort is not labour augmenting and (ii) bargaining coexists with efficiency wage considerations. Refer **Section 3** in the text, where the production function was written as:

$$Y = \exp(\tau_t+\lambda_i t)A_j[E(.)]^{\gamma}D^{\delta}N^{\alpha}K^{\beta}\ v \tag{1}$$

$$E = E(W/P^c,\ W/W^a) = E(W^c,\ W^r) \tag{2}$$

where subscripts 'jt' have been suppressed, E is unobserved daily effort, and we have defined the consumption wage, W^c=W/P^c and the relative wage, W^r=W/W^a for neatness. The problem facing the firm is *max* π = *PY-WDN,* where Y is given by (1), W=wage per day, D=days worked per worker and N=number of workers. Days (D) is taken as independent of the wage (W), for reasons discussed in Section 3.3. of **Chapter 3**. The first order conditions with respect to W and N are

$$\partial\pi/\partial W = P(\partial Y/\partial E)(\partial E/\partial W)-DN = 0 \tag{3a}$$

$$\partial\pi/\partial N = P(\partial Y/\partial N)-WD = 0 \tag{3b}$$

which imply $PY(\partial \log Y/\partial \log E)(\partial \log E/\partial \log W) = WDN = PY(\partial \log Y/\partial \log N)$ which, by (1), gives the effort-wage elasticity,

$$\varepsilon_{EW} = (\partial \log E/\partial \log W) = (\alpha/\gamma) \tag{4}$$

In the special case when effort is specified as labour-augmenting (α=γ), the effort-wage elasticity is unity, which is the Solow condition. In fact, ε_{EW} may deviate from unity even if effort is specified as labour-augmenting. This is the case when wage determination involves both efficiency wage considerations and bargaining. The intuition is straightforward. Imposing bargaining on an efficiency wage setting will result in an agreed wage in excess of the efficiency wage. To the right of the optimum or efficiency wage, the effort function shows decreasing returns to wage increases. Therefore, for any increment in this wage, the increase in effort will be less than proportional. In the standard model, $\varepsilon_{EW}<1$ and in our more general model, $\varepsilon_{EW}<(\alpha/\gamma)$.

We are now in a position to develop the condition that efficiency wages pay for themselves. Taking logarithms of equation (2) and using the Taylor series expansion to first order gives

$$\log E = c + \kappa_1 \log W^c + \kappa_2 \log W^r \qquad (5)$$

Using the definitions of W^c, W^r in (2), this implies

$$\varepsilon_{EW} = \kappa_1 + \kappa_2 \qquad (6)$$

Substituting (5) into the log-linearized form of the production function (1), we get:

$$y_{jt} = \tau_t + \lambda_i t + a_j + \gamma[\kappa_1 \log(W_{jt}/P^c_t) + \kappa_2 \log(W_{jt}/W^a_t)] + \delta days_{jt} + \alpha n_{jt} + \beta k_{jt} + \varepsilon_{jt} \qquad (7)$$

which is equation (3) in the text. From (4) and (6) we have that

$$\gamma(\kappa_1 + \kappa_2) = \alpha \qquad (8)$$

This is the condition that efficiency wages pay for themselves. It requires that the sum of the coefficients on the efficiency wage terms equals the coefficient on employment. If wages are bargained then, by the argument spelt out above,

$$\gamma(\kappa_1 + \kappa_2) < \alpha \qquad (9)$$

The size of the observed inequality is a measure of the importance of wage bargaining. This is why finding that the sum of the coefficients on the wage terms is not significantly different from the coefficient on employment undermines the importance of wage bargaining. Of course, either κ_1 or κ_2 may be set to zero, depending upon the specification of the effort function.

CHAPTER 7
CONCLUDING REMARKS

We have analyzed the fundamental structural relationships that characterize the urban labour market in India and thrown the weight of this analysis against recent developments. The methods used are relatively robust. Our findings reveal the limitations of textbook conceptions of the labour market, and challenge some entrenched views regarding both India and less-industrialized countries in general. In this chapter, we first summarize the work done and point out some of its limitations. We then proceed to place our findings in their broader context. In view of space constraints, we consider the implications of *selected* results. The reader is referred to the concluding section of each chapter for a fuller and more articulated discussion.

Summary and Limitations

In Chapter 2, we explain the persistence of large differentials in unemployment rates between urban sectors of the Indian states, and identify the processes generating the stability of the geographic distribution. Our main contribution probably lies in picking out an altogether neglected question in the Indian context and in producing an alternative to the straightforward equilibrium/disequilibrium hypotheses. We have developed a three-sector model that incorporates rural-urban and urban-urban interactions and so, is of particular relevance to less industrialized countries. This is an extension of the two-sector model of Jackman, Layard and Savouri (1991) who, in turn, complete the Harris-Todaro model by endogenizing wage determination. There is no similar work on unemployment in India or, indeed, any other country. By virtue of extending the Harris-Todaro (HT) framework and producing estimates of the naive HT model, this analysis may be regarded as an evolution of the literature on migration, urbanization and unemployment in less-industrialized countries (see Todaro, 1994 for a discussion of this literature).

We have investigated whether high unemployment in a region results in (a) out-migration of labour and (b) downward pressure on wages in that region. But we have left unexplored, the related question of whether it stimulates in- or out-migration of firms. An enquiry into the (historical) determinants of the distribution of industrial capital in India is a huge but potentially rewarding task. A richer specification of amenity variables is desirable; we have not exploited all available data sources (eg.,the Census of India). We have neglected to explore the phenomenon of migration between the rural sectors of different states, the relevance of which might be considered in future work. Given a segmented labour market, it would be interesting to find out which segment migrants target, if indeed a single segment dominates. Such information would, amongst other things, enable a more accurate characterization of the wage in the structural model. Finally, although we find that barriers are not significant in the long run, the extent to which they slow down migration remains to be understood.

In Chapters 3 and 6, we have investigated wage determination in the factory sector. Our contribution lies in conducting the first theoretically motivated study of wage determination in Indian manufacturing. Layard, Nickell and Jackman (1991, Annexe 3.1) construct a model of imperfect competition in the labour market that introduces efficiency wage considerations into a bargaining framework. They solve this for unemployment. In Chapter 3, we modify their specification to incorporate factory size and visible effort, and solve for wages. In Chapter 6, we conduct a direct investigation of the efficiency wage hypothesis that, to our knowledge, is the first such in the context of a less industrialized nation. Here, we modify the Solow condition to take into account the possibilities that effort is not labour augmenting and that bargaining coexists with efficiency wage considerations. Under these conditions, the effort-wage elasticity is less than unity and its size affords a means of discerning the importance of bargaining. Efficiency wages may contribute to explaining the formal-informal sector wage dualism in urban India.

This analysis suffers from the absence of data on worker (and job) characteristics. In addition to the identified variables, fixed effects play a very significant role in determining the industry and state earnings distributions. We are able to explain the state fixed effects fairly well but face prohibitive data constraints with regard to explaining the industry fixed effects. It would be useful to be able to allocate industry fixed effects between compositional attributes of the work force (gender, skill), union power and technological features that motivate efficiency wage setting. A further unsatisfactory feature of this analysis is that there are no annual data on unemployment in India and the quinquennial time series is very short. Although we are able to identify a significant effect of unemployment on the wage, our estimate of its size lies in a range. We are unable firmly to establish the role of unions in wage determination. Although industry-state level union data would have helped, this is an inherently complex question, basically because power is difficult to quantify. There are recognized shortcomings of membership and dispute statistics. In addition, unions in India's factory sector appear to have manifest themselves primarily by seeking and enforcing labour legislation and by successfully claiming cost of living adjustments to wages. Finally, further work is desirable on the question of why efficiency wages are needed to elicit effort. Important questions of the health and nutrition standards of workers at one end and of job security at the other, are potentially tied in with an understanding of this[1].

The trend growth rate of employment during 1979-87 was -0.3% p.a. as against about 3.5% p.a. in the preceding decade, even though output growth accelerated from less than 5% p.a. in the 1970s to 6.6% p.a. in the 1980s and the growth rate of capital did not change significantly. So, more was produced with less. While the implied surge in productivity has been celebrated as a consequence of early steps in the liberalization of economic policy in India, observation of a decline in the 'good jobs' available in the economy has raised doubts regarding the desirability of the policy changes initiated in the 1980s. Apart from the immediate redundancy of about 200 000 workers, the long run performance of factory employment is important because factories offer a good part of the scarce regular employment in India. Almost 10% of India's urban labour force is chronically unemployed or underemployed (Chapter 2). A further 12% are in casual employment where there is

[1] Do firms need to pay efficiency wages because workers are *unable* to work hard unless they are paid uncompetitively high wages, or are they all shirkers in the knowledge that their jobs are secure ?

considerable income insecurity and the daily wage is, on average, 0.4 times that in regular employment (Sarvekshana 1990). Chapter 4 was motivated to explain the decline in factory sector employment in the 1980s. Ours appears to be the second analysis of the data, the first being a World Bank study. Our analysis contends their central claim and offers an alternative explanation of events. It goes some way towards establishing the relation between the policy shift and the slowdown in employment growth and enables us to think about longer run employment prospects.

Parts of this analysis are speculative and demand further research. We are missing a full understanding of the political economy of change in the 1980s as well as firm-level detail on some facts and mechanisms. Thus, for instance, it would be useful to know what causes changes in actual days worked by the factory and in particular whether it is a decision on the part of the employer or whether it is largely exogenously determined by, say, the rate of power-cuts. Although we have established that the entire factory sector and, in fact, the entire manufacturing sector suffered lower employment growth, there is considerable inter-industry variation in the time profile of employment. Being occupied with the broader-scope question, we have neglected to analyze this. An industry-level analysis based on a longer time series may yield interesting insights.

Our analysis of employment behaviour motivates us to investigate the underlying technology. In Chapter 5, we estimate production functions that provide useful insights into product market structure and the productivity effects of higher work intensity. Based on the obtained production elasticities, we estimate total factor productivity growth (TFPG) for the aggregate factory sector and its two-digit industries. A somewhat unusual feature is that we are able to control for *actual* time worked per worker. Our TFPG estimates take account of imperfect competition in product markets, neglect of which flaws existing estimates of TFPG in Indian manufacturing.

As the assumption of common-slopes in a production function may be especially restrictive, we estimate industry-specific production functions but, at this level, insufficient degrees of freedom force compromises upon us. Future work can overcome this problem by pooling three-digit industry-state data for each two-digit sector. The process of liberalization, begun in the late 1970s, received a sharp boost in 1991 with the introduction of the *new economic policy* under IMF conditionalities. As more recent data become available, it would be interesting to investigate whether the increase in TFPG observed in 1979-87 continued or accelerated after 1991.

Results and Implications

1. There is an inter-state urban-urban disequilibrium that is maintained by the existence of an intra-state rural-urban equilibrium. Interstate migration out of high unemployment cities is offset by migration into cities from their rural hinterland. While barriers are not a serious inhibiting factor, adjustment speeds are finite, which is why the urban sector of any state is unable to 'run away' from its rural sector.

2. As under the straightforward disequilibrium view, interventions directed at employment creation are justified. Whether these should be located in the rural or urban sectors of high unemployment states, or both, is an open question.

3. There exist two distinct unemployment-wage relations and they are identified once appropriately specified. Existing studies tend to identify one or the other of the two curves and we know of no other study that identifies both.

4. From our three-sector model, we derive a migration equilibrium condition (or long run supply curve). This embodies the idea that, for given amenities, regions with higher wages attract higher unemployment. It is consistent with Harris and Todaro (1970) and Hall (1970), though we argue that their models are incompletely specified.

5. We also identify a wage-setting function (or short run supply curve) which incorporates a negative effect of regional unemployment on wages for given productivity and wage pressure variables. This increments the accumulating evidence of effects of similar size in a diverse set of countries (Blanchflower and Oswald, 1994). The result is of particular interest in India, given widespread notions of the insulation of factory workers from the market outside (eg., Holmstrom, 1975).

6. The long run labour market equilibrium in a region is determined by the intersection of

the long and the short run supply curves. From the implied reduced form equations it follows that unemployment in a region is increasing in wage pressure and amenities.

7. In view of sizeable inter-state differences in labour force composition in India, the estimated equations allow for compositional effects. So as to take account of widespread underemployment in India, we have used two alternative measures of unemployment. The usual status rate only counts persons who have been unemployed for most of the year but the daily status rate captures, in addition, person*days* of underemployment.

8. Although the smallness of the data sample deems that the results be regarded as tentative, they are altogether very plausible. Some of these results deserve consideration:

(a) It appears that workers do not like leaving the left-wing states of Kerala and West Bengal, possibly on account of their superior social infrastructure or their protective governments.

(b) Our wage equation estimates show that, *ceteris paribus*, there is no evidence of public sector firms offering wage premia. Yet, people queue for public sector jobs, presumably because of their non-wage perquisites, especially job security.

(c) The urban labour market appears segmented for casual/regular, young/old and literate/illiterate workers.

(d) Since, *ceteris paribus*, the proportion of 15-29 year-olds raises daily but not usual status unemployment, we may conclude that the young face frequent short spells of unemployment before they settle into regular jobs. In the absence of duration data, this is a useful insight.

(e) We find that unemployment amongst the illiterate is significantly lower than amongst the literate, surely a reflection of lower reservation wages and the imperative to earn a living. However, we find no significant differences in unemployment within the literate group. This undermines the hypothesis put forward by Blaug *et al* (1969) which has encouraged a tendency to neglect unemployment statistics in India on the grounds that they merely reflect luxuriously long search by the highly educated.

(f) Rural unemployment appears to spill over into urban unemployment. For *given* rural unemployment, a higher proportion of landless rural workers results in higher urban unemployment, demonstrating the greater mobility and lesser choices of this group. This result makes the case that urban unemployment will be ameliorated by land reform and/or the creation of non-agricultural employment in rural areas.

(g) While the urban labour market has its complexities, to some extent it mirrors the rural labour market. Thus it has been suggested (Deshpande, 1992) that differences in access to land and education in the rural sector differentiate the stream of migrants. In the urban economy, the illiterate and landless take casual employment while the better-off tend to get regular jobs.

9. There was a marked acceleration in real earnings of factory workers in the 1980s and this has generated surprise and called for analysis (eg., Ahluwalia 1991, p.83), there being *no* analyses of wage determination in Indian manufacturing. We find that work intensity, the cost of living, productivity and size can explain more than almost 90% of earnings growth. Of particular interest to our investigation of declining employment in this decade, work intensity (or *days*) explained more than a third of real earnings growth.

10. The dependence of wages on unemployment implies that the factory sector faces an upward sloping wage-setting curve, not the perfectly elastic labour supply curve that is still commonly assumed in the literature on less-industrialized economies.

11. Although excess supply on the labour market depresses wages (5), the labour market does not clear: there is substantial unemployment[2]. Our analysis suggests that factory jobs generate queues of unemployed, from which it appears that they offer uncompetitively high wages. Dramatically large and stable disparities in factory earnings across industry and state further undermine the competitive model.

12. Aggregate variables encapsulated in the time dummies have no significant impact on wages at the industry-region level, which is probably a reflection of labour market segmentation. This is supported by our finding that the average wage in the region serves as a comparison or alternative wage for workers in a factory.

13. Industry variables, namely productivity and average factory size, have a positive and well-determined impact on wages. In addition, wages are increasing in the wedge between consumer and producer prices, which is large in a developing country like India. These

[2] *Usual status* unemployment cannot really be deemed frictional.

results are consistent with efficiency wage and bargaining models but are difficult to reconcile with perfect competition.

14. In independent specifications, effort appears to respond to increases in relative wages and absolute consumption wages. However, in a competition between the two, the absolute consumption wage is the winner. In any case, there is support for the ***modified*** nutrition-efficiency wage hypothesis that we propose.

15. The evidence is that efficiency wages are paid in Indian factories, and they appear to pay for themselves. The latter finding undermines the importance of wage bargaining.

16. In any case, factory wages are not institutionally determined and rigid[3], as assumed by paradigm-setting models of development (eg. Lewis, 1954 and Harris and Todaro, 1970).

17. Since wages are not market-clearing irrespective of government interventions, analyses that recommend the removal of all state machinery in the labour market as a cure for its ills are likely to be barking up the wrong tree. If unions in particular do not play a significant role in bargaining high wages, they could make an important positive contribution in protecting worker safety and working conditions and in monitoring adherence to labour laws.

18. Imperfect competition in the labour market has potentially serious consequences. To the extent that productivity gains are shared with workers, they do not translate into higher employment in the short run. However, we find that higher wages induce higher productivity (15). Depending on the demand elasticity, this may stimulate employment. Higher wages also feed back into higher demand for manufactures.

19. These findings are interesting in light of the 1980s experience of rapid growth in wages and productivity coupled with a collapse of job creation in the factory sector. We have argued that wage acceleration is not the major explanation of the employment decline. This view is strengthened by finding that higher wages in this decade paid for themselves by inducing higher productivity.

20. In the arid territory of analyses of the 1980's employment decline, a 1989 World Bank

[3] This is not to say that institutions have *no* role in wage determination.

study sticks out. It claims that accelerating wages clamped employment growth and that unions and labour laws drove the growth in wages. We counter both claims, the first in Chapter 4 and the second in Chapter 3. This is important because World Bank studies tend to influence policy.

21. Our estimates of an employment function on a panel of industry-region data pertaining to the 1980s show that, given rapid output growth, wage growth cannot explain the decline in employment. Neglecting to control for work intensity creates a powerful bias on the wage elasticity, which is what misled the Bank. The strong drag arose from something common across manufacturing industries in this period (time dummies). We argue that this is the result of (i) improvements in public infrastructure and (ii) the competition shock arising from deregulation that was phased in through the 1980s.

22. How did these changes operate? We argue that there was an increase in (i) unobservable effort and (ii) time worked per worker (or *days*). Hence more production was possible without more workers.

23. Why would unobservable effort have increased in the 1980s ?: (i) job-losses will have signified worsening labour market conditions for factory workers; (ii) union power was on the decline and the government was implicitly withdrawing its support for workers; and (iii) wages were rising. The last gains support from our finding of efficiency wage effects (15). Uncertainty associated with the reform process may have encouraged employers to raise wages as opposed to employment. It would be interesting, in future work, to investigate efficiency wage effects in the 1970s, a period when both product wages and real productivity evolved sluggishly in comparison with the 1980s.

24. *Days* increased on account of (i) dehoarding of labour stimulated by a new imperative to cut costs; (ii) greater uncertainty; and (iii) less working time being lost as a result of work stoppages. The following findings, emanating from Chapters 3-6, lend support to this claim:

(a) The data show that, between 1979-87, the increase in *days* was equivalent to a switch from a 5 to a 6 day week. Since there was no legislated increase in working time, this must be a result of less work stoppages and decentralized agreements on working longer hours.

(b) In at least 9 of 18 sectors, industry production function estimates are consistent with dehoarding of labour in growing industries and involuntary hoarding or firing restrictions in declining industries (Chapter 5). Further evidence of hoarding is adduced from our estimate of the *days* elasticity of the wage, which indicates, on average, a fair amount of 'undertime' work (Chapter 3).

(c) The costs of adjustment are significantly greater for employment than for *days*. In the year following a shock, while less than half of the desired adjustment in employment is effected, the adjustment of *days* is virtually complete (Chapter 4).

(d) Additional *days* are more productive than additional workers (Chapter 5), while at the same time being less expensive (Chapter 3). The latter may seem surprising as one naturally thinks of increases in *days* (or hours) as reflecting overtime work, which claims a wage premium. The finding that an additional day worked increases *earnings* less than proportionately (specifically, by 50%) suggests that extra days may represent a recuperation of reductions in time worked that were *not* associated with reductions in wages. Time lost on account of power shortages fits this picture (Chapter 3).

25. (a) To the extent that the slowdown in employment growth is related to higher unobserved effort on the part of workers, the long run effect on employment is ambiguous unless further structure is imposed on the model. Higher effort levels lower the wage in efficiency units and so raise the demand for labour but, when every worker is more productive, one needs fewer workers per unit of capital. The net effect depends upon the labour demand elasticity.

(b) To the extent that the slowdown is due to rising *days*, its consequences, good and bad, are bound to be shortlived since there is a natural ceiling to growth in *days*. The data show that, after reaching a deep trough in 1986, employment growth was positive in 1987-1989.

26. The finding that an additional day worked represents an increase in labour *and* capital utilization is of considerable interest, given that capital is scarce and that Indian industry has a chronic affliction of excess capacity. Moreover, since higher capital utilization makes workers more productive, *ceteris paribus* it improves employment prospects.

27. Workers are paid less than their marginal product. This 'exploitation' signifies imperfect competition in product markets (Robinson, 1933) and provides an estimate of the markup

of price on marginal costs.

28. There are substantial inter-state productivity differences even after controlling for industrial composition (Chapter 3). We argue that this is unsurprising in a developing economy. Persistent differences in manufacturing efficiency between states appear related to their labour force composition (education, age), their structural attributes (infrastructural development, agglomeration of production, unemployment) and their industrial relations record (disputes and possibly absenteeism) (Chapter 5). Human capital theory alone would explain only a small part of the productivity differentials. A striking case in point is Kerala which now has virtually universal literacy as compared with, for instance, Bihar which has a very low literacy rate: Bihar's manufacturing productivity is well above the national average and Kerala's well below.

29. Total factor productivity growth in factories during 1979-87 is estimated to lie in the range 2.4%-3.8% p.a., with our investigations pointing to the lower end of the range. In the same period, the growth in *days* was 1.7% p.a. The contribution of productivity to output growth was 36-60%, with *days* contributing an *additional* 18-25%. This is remarkable, not only relative to India's past record, but also relative to other developing countries.

30. By invoking greater time and effort input by workers, we have adopted a more 'social'[4] view of the causes of productivity growth than has so far occurred in the Indian literature. Since productivity gains from increasing days are not sustainable, the rewards from the new economic policies may have been somewhat exaggerated.

Overall, the thesis develops a complete and rigourously parametrized picture of the labour market in urban India. Unemployment is an important economic and social variable that cannot be bundled away as a luxury. Wages are not institutionally fixed and exogenous. Product and labour markets interact and both are imperfectly competitive. Appreciation of these facts does not seem to have filtered through to any applied work on India. It is hoped that this work, which is only preliminary, will inspire further analyses of India and other less-industrialized economies.

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[4] Akin to that of Weisskopf, Bowles and Gordon (1983).

DATA APPENDIX: DEFINITIONS AND SOURCES

Notes on data and variables and a guide to **Notation and abbreviations** follow the **Table of definitions**. An asterisk on the variable name indicates that it pertains to the *factory sector* (see **Notes** below). Acronyms for sources: ASI=Annual Survey of Industries, CMIE=Centre for Monitoring of the Indian Economy and NSS=National Sample Survey.

Variable	**Definition**
Variables available by state (*s*)	
age	proportion of urban males in the 15-29 year old age group; NSS.
*alternative wage** (W^a)	state-average of factory production-worker wage, given by $\Sigma_i[N_{is}/N_s]W_{ist}$, where W_{ist} is *wage*.
caste	proportion of urban population in the designated category of 'scheduled castes or tribes'(SC/ST); CMIE.
casual labour	proportion of urban male labour force in casual employment; NSS.
construction labour	proportion of urban households whose main activity is construction; NSS.
higher education	proportion of urban males with secondary, graduate or higher level qualifications; NSS.
infrastructure	index including measures of power supply, roads, post offices, banks, schools, irrigation, etc.; CMIE.
labour force(R/U)	ratio of rural to urban labour force (15^+ population); NSS.
landless	proportion of agricultural labour force that is landless. *Agricultural labourers* in CMIE; CMIE.
left wing	a dummy that takes the value 1 for Kerala and West Bengal.
literacy	urban male literacy rate; CMIE.
metropolis	a dummy that takes the value 1 for West Bengal, Maharashtra and Tamil Nadu.
$\Delta ln(NDP_{st})$	yearly change in logarithm of state net domestic product; Chandhok *et al* (1990).

poverty	proportion of urban population below a state-specific nutrition-based poverty line; Minhas *et al* (1990).
public sector	ratio of fixed capital in public companies to that in private registered manufacturing in 1987/88; CMIE (1990).
regular	proportion of regular workers in urban male labour force; NSS.
rural density	rural population per acre of land; CMIE.
rural wage	average labour productivity in agriculture; *Alternatives:* average wage of males performing agricultural work and average rural wage; CMIE *Deflated* by price index with base=India in 1972. Computed like deflator of urban wage (see *wage*); based on Minhas *et al* (1990).
rural UR	state-level rural male unemployment rate: daily & usual status. See **Notes** below; NSS.
self-employed	proportion of self-employed in urban male labour force; NSS.
URDS, URUS	state-level urban male unemployment rate, measured by daily status (URDS) and usual status (URUS). See **Notes** below; NSS.
*strikes**	persondays lost per factory worker on account of strikes. *Alternatives:* dispute duration, union density; Indian Labour Yearbook and Indian Labour Statistics, Labour Bureau.

Prices

consumer price index (P^c_{st} *or* CPI_{st})	state-level index of prices of food, tobacco, fuel and housing for industrial workers. There are separate indices for urban non-manual employees and for agricultural labourers; Chandhok *et al* (1990).
*industry price** (P_{it}, P_{st})	wholesale price index at the 2-digit industry-level (P_{it}). Using weights Q_{is}/Q_s, where Q is output, we compute P_{st}; Chandhok *et al* (1990).

Variables available at the industry-state (*is*) level

*capital stock** (*K*)	gross fixed stock at replacement prices; Aggarwal (1991), ASI and Chandhok *et al* (1990). See **Notes** below.
*days** (*D*)	days actually worked per worker (M/N), where M=*mandays* and N=*workers*. See **Notes** below; derived.
*earnings**	annual income per worker (wage-bill/*workers*); derived.

employees*	production workers plus 'supervisory staff'. Defined as 'total persons engaged' until 1980; ASI.
loans*	total value of outstanding loans; ASI
mandays* *(M)*	total days *actually* worked by all workers or employees, as the case may be. A day is 8 hours. See **Notes** below; ASI.
$\Delta ln(Y_{it})^*$	change in logarithm of industry output deflated by P_{it} (see *industry price*). Proxies cyclical demand changes (σ). *Alternatives*: change in state output; deviations of demand from trend at the industry and state levels; derived.
output* *(Q)*	total output; ASI.
productivity* (π)	value-added per worker (Y/N) in the factory sector. *Deflated* by P_{it} when $(Y/N)_{ist}$ and by P_{st} when $(Y/N)_{st}$; derived.
skill*	ratio of *employees* to *workers*; derived.
Δtfp^*	total factor productivity growth, obtained as $\Delta y - \beta_n \Delta n - \beta_k \Delta k - \beta_d \Delta days$. Lowercase letters denote logs, Δ denotes the first difference and the β's are output elasticities estimated in **Chapter 5;** derived.
value added* *(Y)*	nominal difference of value of outputs and inputs. Gross preferred to net because depreciation figures are unreliable. Deflated by the output price, P_{it} (see *industry price*), in absence of industry value added deflators; ASI.
wage* *(W)*	*daily* wage of production workers (*earnings/ mandays*). Deflating by P^c_{st} gives the *consumer wage*. To obtain the *product wage*, we deflate by P_{it}; derived.
workers* *(N)*	Production workers. See **Notes** below; ASI

Time and cross-sectional dummies and trends

fixed effects (θ_{is} *or* θ_s)	time-invariant effects specific to industry-state or state.
time dummies (θ_t)	vector of year dummies.
industry trends ($\lambda_i t$)	vector of industry-specific linear trends. Correspond to industry dummies in a first-differenced equation.
state trends ($\lambda_s t$)	vector of state-specific linear trends. Correspond to state dummies in a first-differenced equation.
industry-time dummies (θ_{it})	vector of TxI dummy variables where T is the number of years and I, the number of industries in the sample.

NOTES ON DATA AND ON SOME VARIABLES

Regional (or state) panel

The data used in **Chapter 2** consist of 14 states observed quinquennially in the years 1972/73, 1977/78, 1983 and 1987/88, corresponding to the employment-unemployment surveys of the National Sample Survey Organization (NSSO). In 1983, the survey was conducted for the calendar year, while in the other years it covered the June-July period, straddling two years. For neatness, we refer to the four years as 1972, 1977, 1983 and 1987. The design and definitions of the surveys for 1977/8, 1983 and 1987/8 are strictly consistent and those for 1972/3 are broadly comparable (see **Notes** on unemployment below). There are no reliable annual data on unemployment in India.

Industry-state panel

The data used in **Chapters 3-6** are a panel of 18 two-digit industries disaggregated by their location in 15 major states of the Indian federation. These 270 cross-sections are stacked for a period of 9 years, 1979/80-87/88 (referred to as 1979-87). *Electricity* is, strictly, not a manufacturing industry but it is included in the sample because its performance impacts on other industries and because it is the one two-digit industry that is entirely in the public sector. *Jute textiles* is removed on account of its having a large number of missing values. In 1985, it accounted for 1.2% of value added in manufacturing. The remaining 17 industries account for more than 98% of value added in registered manufacturing. Industry-state units for which value added was found to take a negative value are deleted since their logarithms are undefined. Therefore the data panel is often unbalanced, but the software used can deal with this (see Arellano and Bond, 1988).

Size structure of manufacturing in India

The *factory sector* is synonymous with the *registered* or *formal* or *organized manufacturing sector*. It includes all enterprises with at least 10 employees with power or at least 20 without. It comprises the *census sector* and the *sample sector*, the names arising from the manner in which the Annual Survey of Industries (ASI) surveys them. The census sector comprises the larger factories, with at least 50 workers with power or at least 100 without, and smaller factories are in the sample sector. Non-factory manufacturing establishments fall into the *unregistered* manufacturing sector, on which there are no consistently available statistics. It is estimated that, in 1974/75, the share of the factory sector in *urban* manufacturing was 55% in terms of employment and 84% in terms of value added. In the same year, its employment share in *total* (rural+urban) manufacturing was 28% and its value added share, 74% (Sundaram and Tendulkar, 1988).

Unemployment rates

The NSS produces estimates of unemployment by three alternative measures, designed to capture the different facets of unemployment in India. These are the usual, weekly and daily status rates. In **Chapter 2**, we employ the usual and daily status measures. For the *usual status unemployment rate (URUS)*, the reference period is the previous year and the criterion is major time spent. So, those persons are counted as having been unemployed who, for the largest chunk of their time in the 365 days prior to the survey, were unemployed. In 1972 alone, the usual status definition was different and referred to 'the status which prevailed over a long period in the past and which is also likely to continue in future'. For comparability of the later 3 years with 1972, the NSS provides an *adjusted usual status* measure that purges the unemployment rate of those persons who worked regularly but in a subsidiary capacity. Since the 1972 definition strikes us as rather vague, we have chosen to use the unadjusted figures. The *weekly status* rate is defined just like the usual status rate but with a reference period of a week. To obtain the *daily status* (*URDS*) rate, enumerators ask those people who are classified as employed by a weekly time-spent criterion to look back to the week before the survey and report, in half-day units, the proportion of the week for which they were unemployed. It is a *personday* rather than a *person* rate of unemployment and it picks up short spells of unemployment that the usual status measure does not.

Workers

On average, production workers comprise two-thirds of all employees. Casual and permanent workers are included in an approximate ratio of 1:9. In practise, the number of casual workers is likely to be understated, especially when many work for only a fraction of the year. Unfortunately, there is no information on the changing age, sex, education and skill composition of the work force.

Days worked per worker or employee (days)

The official definition of *mandays* is '*days worked rather than days paid for*, obtained by adding up the number of persons attending in each shift over all shifts worked on all days, working and non-working' (CSO, 1987/88). A manday is standardized as 8 hours. We refer to mandays per worker (or employees: clear from context) as *days* or *work intensity*. *Days* averages overtime and undertime both across workers and temporally, over the course of a year. *Days* will register an increase if, for example, workers begin to work more than one shift per day, the number of annual holidays is reduced, absenteeism rates fall or there is a lower incidence of work stoppages on account of power shortages, materials bottlenecks, machine faults or industrial disputes.

Capital stock

The ASI reports the book value of *capital stock* (K_{ist}) which is net stock at historic costs but we want gross fixed stock at replacement cost. We want gross and not net fixed capital because the depreciation figures reported in the ASI are the rates allowed by the income tax authorities and are seldom representative of true capital consumption (eg., Banerji 1975, p.18). Working capital is excluded on the considerations that (a) the relation between output and working capital is less influenced by technological factors than is that between output and fixed capital and (b) the composition of working capital is such that it is difficult to arrive at a suitable deflator (see Goldar, 1983). Aggarwal (1991) has constructed the gross stock at replacement cost (K^*_{it}) for 3-digit industry groups using the perpetual inventory method with three asset types individually deflated and with reference to a benchmark for 1960-61. We have aggregated the 3-digit data to the 2-digit level. The 3-digit data typically accounted for *at least* 75% (and more often than not, 90%) of unadjusted capital in the 2-digit sector and the total was blown up proportionately. Where Aggarwal's three-digit sample covered too small a fraction of the two-digit industry, only partial adjustment of the book value of capital was possible. In these cases, we deflated the book value data by the wholesale price index for machinery and equipment (Chandhok *et al*, 1990). Aggarwal's estimates cover the period 1973-1986. To obtain adjusted estimates for 1987, we extrapolated the series for each industry, relying upon the ratios of unadjusted to adjusted stock. Using the ratios that obtain in the book value data, the adjusted 2-digit industry capital stocks were disbursed by location across the major states. The fact that the panels used are short may be argued to be an advantage since inflation and technical progress make correct measurement of capital services more difficult for long time series (Feldstein, 1967). It may be argued that it is incorrect to use fully adjusted capital for some industries and partially adjusted capital for others. However, the two series are very nearly linear trends with insignificantly different growth rates. Levels differences between the series are taken care of by industry-state fixed effects in the estimated models. As these procedures are far from satisfactory, an instrumental variables estimator is used to ameliorate the effects of any measurement error in the adjusted capital stock series.

Notation used in the Tables and Commonly used Abbreviations

Figures in parentheses under coefficient estimates are the absolute t-ratios associated with them. Instruments are listed in Notes to Tables. *x(a,b)* denotes that instruments include lags of x running from x_{t-a} to x_{t-b}. The p-values associated with test statistics for serial correlation (*srl corr*) and the Sargan and Wald tests are reported in parentheses after the test-statistic. Thus, for example, Sargan= 0.68/62 (0.28) indicates that Sargan's χ^2 statistic is 0.68 and, for 62 degrees of freedom, the p-value is 0.28. The test-statistic for first-order serial correlation in the differenced residuals is significantly negative in all our GMM equations. Hence, it is not reported.

ASI	Annual Survey of Industries	LIEs	less industrialized economies
CMIE	Centre for Monitoring of the Indian Economy	log	logarithm
CSO	Central Statistical Organization (India)	ME	measurement error
FD	first-differences	NCAER	National Council of Applied Economic Research
GOI	Government of India	NSS(O)	National Sample Survey (Organization)
GMM	generalized method of moments	OLS	ordinary least squares
IEs	industrialized economies	TFP(G)	total factor productivity (growth)
IV	instrumental variables	WG	within-groups

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