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SPATIAL AND TEMPORAL AGGREGATION IN THE DYNAMICS OF LABOR DEMAND

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ABSTRACT

The paper demonstrates the general difficulty of inferring the structure of adjustment costs from aggregated, including industry data, except in the unlikely case that costs are symmetric and quadratic at the micro level. The implications of this difficulty for cross-national comparisons of adjustment costs, and for attempts to infer the structure of these costs without micro data, are examined.

In the voluminous literature on dynamic labor demand studies based on annual data generally find longer lags than those that use quarterly data, which in turn produce longer lags than models estimated using monthly data. However, when a consistent set of U.S. industry time series is used, and quadratic symmetric costs are assumed, the estimated length of the lag is independent of the frequency of observation. This conclusion is clearly not general: If we assume the costs of adjusting labor demand are lumpy, inferences about their structure differ greatly depending on how often the data are observed.

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I. Introduction

Since its formalization in the work of Holt et al (1960) the theory of the dynamics of labor demand has been based in maximization by a firm that faces shocks to product demand and factor and product prices, and whose adjustment to these shocks is costly. Yet from simple employment-adjustment models to models of rational expectations, the econometric examination of this theory has with very few exceptions been based on data aggregated at least to the industry level and observed quarterly or annually.[1] What are the difficulties that the use of these data, that are highly aggregated both spatially and temporally, imparts to inferences about the dynamics of labor demand?

I consider two issues here. The major one is what these data allow us to infer about the structure of adjustment costs. The conventional specification in these studies is that adjustment costs are convex in the size of the change in labor demand. Yet all five studies that have used micro data to confront this assumption with other alternatives find that the other formulations of adjustment costs perform better. These studies are:

> Hamermesh (1989), who used monthly data on employment in manufacturing plants to run a "horse-race" between the conventional model and a switching model specifying lumpy adjustment costs.
>
> Craig (1990), whose semiparametric tests of monthly data on lumber mills reject smooth adjustment and imply that there are fixed costs of changing the level of employment.
>
> Pfann and Verspagen (1989), who suggest that the typical firm is best characterized as having both fixed and variable costs of adjusting employment (though the annual data make any conclusions highly tentative).
> Holtz-Eakin and Rosen (1991), who specified a rational-expectations model describing the demand for full- and part-time municipal employees over annual data and could not find increasing marginal costs of adjustment (and the convex adjustment costs that they imply).

Hamermesh (1992), who found that a general model including both quadratic variable and lumpy fixed adjustment costs described quarterly data on airline firms best.

The apparent failure of the assumption of smooth adjustment in tests on micro data invites consideration of what more spatially aggregated data can tell us about the structure of adjustment costs. A related issue is what temporal aggregation of microeconomic data does to our ability to infer that structure.

The main reason why these questions are important is that a rapidly growing literature has focussed attention on a variety of aspects of the structure of adjustment costs. The research includes testing for asymmetries, which is linked to inferring the impact of policies that restrict firing; studying cross-country differences to examine whether adjustment is more rapid where these policies are less important; and using these models to infer the magnitude of adjustment costs. In Section II I present several examples that demonstrate that none of these issues can be studied usefully using spatially aggregated data. Section III examines the problems of drawing inferences about them from micro data that are observed at a lower frequency than the decisions by employers that generate the underlying data.

II. Spatial Aggregation and Structural Inference

The typical modern model has the profit-maximizing firm choosing a path for its labor input, L_t, to maximize:

$$(1) \qquad E_0 \sum_{t=1}^{\infty} [F(L_t) - W_t L_t - C(\Delta L_t)][1 + r]^{-t}$$

where E_0 denotes expectations at t=0, W is the per-period cost of labor services, r_t is the firm's rate of discount, and I have normalized the product price to equal one. The standard assumptions are that F', $C' > 0$, $F'' < 0$, $C'' > 0$. For our purposes it is important to note that underlying nearly the entire macroeconometric literature is the assumption, usually explicit, that

$C(\Delta L)$ is quadratic. These assumptions, coupled with static expectations about the future paths of W_t and r_t, underlay the Koyck-type geometric lag that was standard in estimating employment dynamics until the late 1970s. The Euler equations that have become de rigueur for estimation since then and that are based on rational expectations use the same assumption about adjustment costs.

There is nothing inherently wrong with assuming quadratic adjustment costs, any more than with assuming linear approximations to general functions in the absence of better information. It has become a convenience in developing increasingly complex forms for estimating dynamic models with rational expectations. The difficulty is that the evidence shows that the assumption is not justified by studies that use firm-level data. Even ignoring that evidence, it is logically incorrect to make this assumption about the structure of the costs that agents face, base macroeconometric estimates on it, and then infer from those estimates anything about the nature of those costs.

To examine the problems of drawing inferences about the size or structure of adjustment costs from estimates based on aggregated data, I consider three alternative underlying structures of adjustment costs. For all three I assume for simplicity that static-equilibrium employment is determined by the level of current output demand, Y. (The same general point holds in a forward-looking or rational-expectations framework based on a vector of forcing variables, but the demonstrations are more complex.) The only common feature of the three structures is their assumption that adjustment costs are not both symmetric and quadratic. In none of these examples do the results stem from heterogeneity in the firms' adjustment costs: All agents face the same structure of costs. The conclusions are produced solely by the difficulties of aggregation.

Example 1: Symmetric Lumpy Costs of Adjustment

Assume the firm incurs a cost of K whenever it changes its employment level, but that this cost does not vary with the size of the change. The profit-maximizing path of employment is described by:

(2) $L_{it} = L_{it-1}$, if $|y_{it}| < K$,

$L_{it} = Y_{it}$, if $|y_{it}| \geq K$,

where y_{it} is a shock to the i'th firm's labor demand at time t. Let the y_{it} be cross-sectionally and serially independently distributed as:

(3) $y_{it} \sim n(\bar{y}_t , \sigma^2_{y_t})$,

where n denotes a normal density function.[2]

Then aggregating across all (equal-sized) units i yields:

(4) $L_t = g_t L_{t-1} + [1 - g_t] Y_t$,

where:

$$g_t = N(x - a) - N(-x - a) ,$$

and N is the cumulative unit normal, $x = K/\sigma_{y_t}$ and $a = \bar{y}_t / \sigma_{y_t}$. Equation (4) is the standard geometric lag structure that mutatis mutandis has formed the basis for most econometric studies of employment dynamics, except that here the true lag parameter varies over time. Under this structure of adjustment costs, though, the parameter describing the lag arises from the aggregation mechanism, not from optimization by each individual profit-maximizing unit. The parameter describing the distributed lag can be written as:

$$g_t = g_t(K, \bar{y}_t , \sigma_{y_t}) .$$

Higher costs of adjustment can be viewed as an increase in K. The effect on the observed g_t is:

$$\partial g_t / \partial K = n(x - a) + n(-x - a) > 0 .$$

Despite the unusual underlying structure, estimates based on aggregates of firms will suggest that employment demand is more sticky if the costs of adjustment are larger. That suggestion correctly reflects the underlying structural change. Inferences from the aggregates will also, though, be affected by changes in the distribution of the shocks. Assuming a mean-preserving spread in y_{it},

$$\partial g_t/\partial\sigma_{y_t} = -\{[x - a]n(x - a) - [-x - a]n(-x - a)\}/\sigma_{y_t} .$$

Then by the mean value theorem:

$$\partial g_t/\partial\sigma_{y_t} = -2K\{zn'(z) + n(z)\}/\sigma^2_{y_t} ,$$

where $x - a > z > -x - a$.

The derivative $\partial g_t/\partial\sigma_{y_t}$ is negative if $|z| < 1.3$.

Since the average demand shock in an industry is usually very small relative to the variance of shocks within the industry (Leonard, 1987), $|z|$ is probably far below one. Thus a decrease in the variance of demand shocks will increase the apparent stickiness of employment in aggregated data. The finding that adjustment appears slower in estimates based on aggregated data does not permit distinguishing between an increase in the underlying lumpy adjustment costs and a change in the distribution of demand shocks across the units that make up the aggregate. A study based on aggregated data will be uninformative both about the structure of adjustment costs and about the speed with which firms adjust their demand for workers.

Example 2: Asymmetric Quadratic Adjustment Costs

A more familiar case makes the usual assumption that the firm's adjustment costs are quadratic, but relaxes the assumption that they are symmetric. For expositional purposes assume that there are no costs of increasing employment. (Assuming positive but asymmetric adjustment costs in both directions would not alter the results qualitatively.) With quadratic costs of decreasing employment the i'th firm's adjustment is described by:

(5) $$L_{it} = Y_{it}, \text{ if } y_{it} > 0 ,$$
$$L_{it} = \gamma L_{it-1} + [1 - \gamma]Y_{it}, \text{ if } y_{it} \le 0 .$$

The importance of the quadratic term in adjustment costs is reflected in γ. Let the y_{it} be distributed as in (3). Aggregating (5) across all units i again yields (4), except that now:

$g_t = \gamma N(-\bar{y}_t / \sigma_{y_t})$.

Increases in the underlying adjustment costs raise γ, which in turn increases the observed lag parameter g_t:

$$\partial g_t / \partial \gamma = N(-\bar{y}_t / \sigma_{y_t}) > 0 \; .$$

Thus the aggregated data will correctly reflect this change in the underlying structure. Unfortunately, though, they will also suggest that a change in the structure has occurred if there is a change in the variance of demand shocks, for:

$$\frac{\partial g_t}{\partial \sigma_{y_t}} = \frac{\gamma \bar{y}_t}{\sigma_{y_t}^2} . n\left(\frac{-\bar{y}_t}{\sigma_{y_t}}\right) \gtrless 0 \; as \; \bar{y}_t \gtrless 0 \; .$$

If the average demand shock is positive, the observer will attribute an increase in the length of the lag of adjustment of employment in the aggregate data to an increase in adjustment costs, even though it may instead be due to a change in the variance of demand shocks.

Example 3: Linear Costs of Gross Employment Changes

The first two examples dealt with costs of adjusting net employment. Consider a case in which there are (different) linear costs of hiring and firing, so that the cost of adjustment is on gross employment changes. (In modeling this case, which is discussed in Nickell, 1986, I view the firm as having perfect foresight over the future path of demand shocks.) The firm's path of employment can be specified parsimoniously as:

(6) $$L_{it} = Y_{it} \text{ if } Y_1^* > Y_{it} > Y_0^* \; ;$$

$$L_{it} = L_0^* \text{ if } Y_{it} \leq Y_0^* \; ;$$

$$L_{it} = L_1^* \text{ if } Y_{it} \geq Y_1^* \; ,$$

where the Y_j^* are parameters determined by the underlying adjustment costs, and I assume for simplicity that the L_j^* do not vary over time. Let the distribution of the determinants of demand, Y_{it}, be:

(3') $\qquad Y_{it} \sim n(\bar{Y}_t\,,\, \sigma^2_{Y_t})\ .$

Aggregating across all units i:

(7) $\qquad L_t = g_{2t}Y_t + g_{0t}L_0^* + g_{1t}L_1^*\ ,$

where $g_{0t} = N([Y_0^* - \bar{Y}_t]/\sigma_{Y_t})$; $g_{2t} = N([Y_1^* - \bar{Y}_t]/\sigma_{Y_t}) - N([Y_0^* - \bar{Y}_t]/\sigma_{Y_t})$, and $g_{1t} = 1 - g_{2t} - g_{0t}$. In this model the linear adjustment costs ensure that there is no lag in (6) and thus no lagged value of L_t in the aggregate equation (7).

Decreases in Y_1^* and increases in Y_0^* are produced by increases in the cost of hiring or firing. Given the distribution in (3'), one sees easily that such increases will reduce g_{2t}, so that the observed effect in the aggregated data will be a reduction in the response of L_t to Y_t. Consider, though, how a mean-preserving spread in Y_{it} affects g_{2t}:

(8) $\qquad \partial g_{2t}/\partial\sigma_{Y_t} = [h(Y_0^*) - h(Y_1^*)]/\sigma^2_{Y_t}\ ,$

where $h(Y_j^*) = [Y_j^* - \bar{Y}_t]n([Y_j^* - \bar{Y}_t]/\sigma_{Y_t})$, $j = 0, 1$. Except for extreme cases when $\bar{Y}_t > Y_1^*$ or $\bar{Y}_t < Y_0^*$, the derivative in (8) is negative. This implies that the observer will identify a decrease in the responsiveness of L to Y as a rise in the costs of hiring or firing, when in fact the cause may merely be an increase in the variance of the distribution of the shocks across subaggregates.

All three examples in this Section illustrate one specific implication of Theil's (1954) demonstration of the problems of linear aggregation over underlying nonlinear behavioral relations. This difficulty has been pointed out in the estimation of expenditure systems (Muellbauer, 1981; Stoker, 1986), and in generalized rational expectations models (Geweke, 1985). Despite economists' general awareness of it, its importance has not informed macroeconometric estimation of dynamic factor-demand equations.

One cannot use aggregate dynamics to examine or compare the structures or sizes of adjustment costs. Other models could be examined and would yield the same conclusion. Only if one makes the very restrictive, and demonstrably not universally correct assumption that adjustment costs are symmetric and quadratic, can estimates of aggregate employment dynamics be informative about those costs. Only with this assumption can one use aggregate data to infer the dynamic paths of labor, capital and materials inputs (Pindyck and Rotemberg, 1983). It is the only one that justifies basing aggregate estimates of the paths of demand for production and nonproduction workers and for investment (Shapiro, 1986) on the underlying path described by a rational-expectations equilibrium. Without it one cannot infer the size of the adjustment costs facing the typical firm for each of its factors of production. Indeed, without it there is no representative firm for purposes of employment dynamics.

The renascent literature on asymmetric adjustment (e.g., Pfann and Palm, 1988) is not internally consistent. The theoretical model is based on costs like those in the second example; but the estimates use aggregate data, and thus are inherently incapable of shedding any light on the underlying hypothesis of asymmetric costs, since they ignore the problems of aggregation. Couching the firm's maximization under asymmetric costs in a rational-expectations framework does not improve things if the estimation is based on aggregate data. Unless the cycles of the determinants of adjustment costs are identical for all firms, the same criticism applies to the long literature (Tinsley, 1971; Burgess and Dolado, 1989) that postulates cyclically-varying adjustment costs.

Changes in the estimates of aggregate employment dynamics have also been linked (Nickell, 1979) to changes in the structure of the rules regulating employment adjustment. Similarly, differences in those regulations among countries have been tied (Abraham and Houseman, 1989) to estimates of employment dynamics using aggregate data. In each case the authors identify longer estimated lags with more restrictive hiring or firing policies. They may be correct; and the inferences are at least internally consistent with the underlying models that are based on quadratic costs (but see Kramarz, 1991, for reasons why even this may not always be true). As the examples show, though, the estimates may be confounding the effects of labor-market institutions on adjustment costs with the impact of changes in the distribution of shocks across the micro units that make up the aggregates.

III. Temporal Aggregation and Structural Inference

Inferring the problems that temporal aggregation produces for estimating factor-demand dynamics is more difficult than analyzing spatial aggregation. In considering the appropriate degree of spatial aggregation, we know that the firm is the relevant decision-making unit. We do not know what the time intervals are between firms' decisions about whether or not to alter factor demand. Indeed, every study of dynamic labor demand ignores the issue, and assumes that the unit of time in employers' decision-making is the interval between observations in the data that are available for the empirical work. Implicitly some researchers assume that employers revise their factor demand only once a year, while others assume that revisions occur quarterly or even monthly.

No doubt some firms (universities and governments at most times, for examples) make employment decisions on an annual basis. For them the appropriate degree of temporal aggregation may be to annual observations. In most for-profit firms, though, employment plans are likely to be revised more frequently than once a year. Especially in larger firms, where projections of product demand are more refined, and in firms where the fixed costs of hiring are lower, higher-frequency data will match the timing of decision-making better. How much higher is not clear; and determining the frequency of employers' decisions is a very worthwhile future research project. But it is difficult to believe that once-yearly decision-making characterizes very many entities. Quarterly, monthly, or even continuous decision-making about employment demand seem more likely.

In this Section I examine various implications of this assertion (and the lack of evidence means it is only an obiter dictum). In the first part I consider the effects of increasing temporal aggregation on estimates of speeds of adjustment of the demand for labor in response to shocks to expected product demand, under the assumption that adjustment costs are symmetric and quadratic. Next I examine what temporal aggregation does to our ability to infer the structure of those costs when that assumption is incorrect.

Effects on Inferences About Adjustment Speeds

An initial picture of the impact of temporal aggregation is obtained by comparing previous estimates of the lag of adjustment of employment or worker-hours behind expected product demand in the literature. Table 1, based on Hamermesh (1993), summarizes the results of the over 60 studies that produce estimates of the median lag in labor demand from equations of the general form:

$$L_t = \sum_{\tau=1}^{M} \lambda_\tau L_{t-\tau} + \sum_{\tau=0}^{N} \mu_\tau X_{t-\tau} \tag{9}$$

where X is a vector of forcing variables, and the λ and μ are parameters to be estimated. In the simple case when M = 1, the data summarized in Table 1 are just the estimates of t^* from:

$$\lambda^{t^*} = .5 , \tag{10}$$

so that I implicitly assume that the vector of forcing variables represents the employer's expectations about the path of their future value. In cases where

Table 1. Estimates of Median Lags in Studies of Dynamic Adjustment of Employment Demand*

	Frequency of Data:		
	Annual	**Quarterly**	**Monthly**
Mean and Standard Deviation	5.53	1.35	1.18
	(5.45)	(0.78)	(1.01)
Median	3.25	1.50	0.60
Range	(0, 26.3)	(0, 18)	(0.4, 3.4)
Number of Estimates	24	31	8

*Computed from estimates in Hamermesh (1993, Tables 7.1 - 7.3).

$M > 1$, I simulated the time path of L_t in response to shocks to X to infer the median lag.

The median lags shown in the Table are measured in quarters. The studies using annual data generally imply quite long lags of employment adjustment behind shocks to the forcing variables. This is not true for the studies using quarterly or monthly data: In them, the averages of the median lags are around four months. The literature suggests that going from monthly to quarterly observations (among heterogeneous sets of spatially aggregated data) has little effect on estimates of the lag in adjustment, but that aggregating still further to annual observations sharply lengthens the estimated lag.

Of course, though many of the studies underlying Table 1 use some of the same data, none uses exactly the same data and model to generate the estimates at different levels of temporal aggregation. We cannot be sure that the much longer median lags in the studies based on annual data are not just the result of different processes generating the underlying time series used in those studies.

Engle and Liu (1972) estimate identical models describing a vector of macroeconomic variables (including investment demand, but not the demand for labor) using monthly, quarterly and annual data for the United States. Their empirical findings illustrate their analytical results, that there is no a priori bias in the estimated lag due to temporal aggregation. Even in simple geometric-lag models any biases depend on the time-series properties of the residuals in the basic (monthly) equations and on those of the dependent variable.

To examine this issue further, I estimate the same simple model of employment demand for two-digit manufacturing industries in the United States from 1955 through 1989. The basic equation is:

(9') $$L_t = \lambda L_{t-\ell} + \mu_\ell Y_{t-\ell} + \beta t,$$

where ℓ is the length of the time interval between observations, and Y is the forcing variable. Equation (9') represents first-order autoregressions, with the length of the time interval increasing as the frequency of the data decreases. Labor demand is measured by the number of employees, and the forcing variable is the Federal Reserve Board index of industrial production for the industry. Under the simplest assumption about the process generating the Y_t, $\mu_\ell Y_{t-\ell}$ can be interpreted as the product of the long-run response of L to Y and the vector of expectations of all future Y_t.[3]

Table 2 presents the estimates of the median lags (measured in quarters and computed as in (10)) from the OLS estimates of (9') over annual, quarterly and monthly time series on the underlying employment and output variables. Among the 18 industries underlying the estimation, annual data yield longer lags than do quarterly data in exactly 9 industries; they also yield longer lags than the monthly data in 9; and the quarterly data produce longer lags than the monthly data in 10 industries. The results hardly indicate a clear pattern of biases resulting from temporal aggregation! Rather, they show in this particular set of time series that temporal aggregation, while it affects the estimates, does not uniformly bias the estimated lags up.

These two exercises imply sharply conflicting conclusions about the impact of temporal aggregation on inferences about the speed of adjustment of employment demand to shocks. However, both the comparison of inferences from other studies and estimates based on the American time series observed at different frequencies suggest that the implied lags are the same whether we use monthly or quarterly data. All the evidence suggests that, so long as we do not need to resort to annual observations, at least in these simple models our estimates will not differ greatly.

Effects on Inferences About the Structure of Costs

The same fairly neutral conclusion does not apply to the possibility of inferring the existence of nonconvex costs from microeconomic data that are

Table 2. Estimates of Median Adjustment Lags in Two-Digit (SIC) U.S. Manufacturing (in Quarters), 1955-1989

INDUSTRY	ANNUAL	QUARTERLY	MONTHLY
Lumber and Wood Products	4.5	4.4	4.6
Furniture and Fixtures	3.2	2.5	2.7
Stone, Clay and Glass Products	2.7	1.9	1.9
Primary Metals	4.4	5.0	3.0
Fabricated Metal Products	2.7	3.0	2.8
Nonelectrical Machinery	22.7	44.1	100.3
Electrical Equipment	1.9	2.2	2.2
Transportation Equipment	1.1	2.4	1.6
Instruments	3.0	6.2	7.6
Tobacco products	14.2	6.4	2.0
Textiles	2.9	2.3	2.2
Apparel	31.3	20.4	15.0
Paper Products	5.9	3.3	2.9
Printing and Publishing	11.6	8.6	8.4
Chemicals	5.6	7.0	7.2
Petroleum and Coal Products	47.5	10.9	3.2
Rubber	0.0	1.8	1.7
Leather	1.6	2.6	2.7

aggregated temporally. Among the variety of possible specifications of nonconvexity, I again choose the model of fixed adjustment costs in (2). Imagine that we have data on a sequence of monthly observations on the firm's employment, L_t, $t = 1, 2, \ldots, T$, with T divisible by 12. I assume that the firm makes its employment decisions monthly and that its lumpy adjustment costs are such that:

$$\Pr\{L_t = L_{t-1}\} = p \; , \; 0 < p < 1 \; .$$

For T large and $p > .5$, we should expect to see large numbers of doubletons, tripletons and higher-order runs that have $L_t = L_{t-1}$.

Define quarterly observations on employment as:

$$L_t^Q = [L_t + L_{t-1} + L_{t-2}]/3 \; , \; t = 3, 6, \ldots, T.$$

Then the probability that adjacent observations on L_t^Q will be equal (and presumably suggest to the observer the existence of fixed costs) is:

$$\Pr\{L_t^Q = L_{t-1}^Q\} = p^5 \; .$$

In the sequence of T/3 quarterly observations:

(11) $$\Pr\{L_t^Q = L_{t-1}^Q \text{ for at least one t}\} = 1 - [1 - p^5]^{T/3 - 1} \; .$$

With $p = .5$, the event in (11) will occur with a probability of at least .5 only if there are at least 68 years of data, 14 years of data if $p = .7$, and 5 years of data if $p = .9$.

Define annual observations on this process as:

$$L_t^A = [L_t + \ldots + L_{t-11}]/12 \; , \; t = 12, 24, \ldots, T.$$

The probability that adjacent annual observations on L will be equal is:

$$\Pr\{L_t^A = L_{t-12}^A\} = p^{23} \; .$$

In the sequence of T/12 annual observations on L:

(12) $$\Pr\{L_t^A = L_{t-12}^A \text{ for at least one t}\} = 1 - [1 - p^{23}]^{T/12 - 1} \; .$$

Even for p quite close to 1, the event in (12) is very unlikely. If $p = .7$, over 30,000 years of data are required before there is a 50 percent chance of its occurrence, and for $p = .9$, 102 years of data are required.

Figure 1a. Monthly Data, K=.1

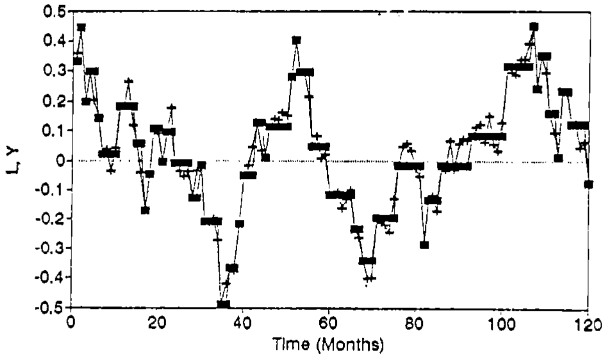


Figure 1b. Quarterly Data, K=.1

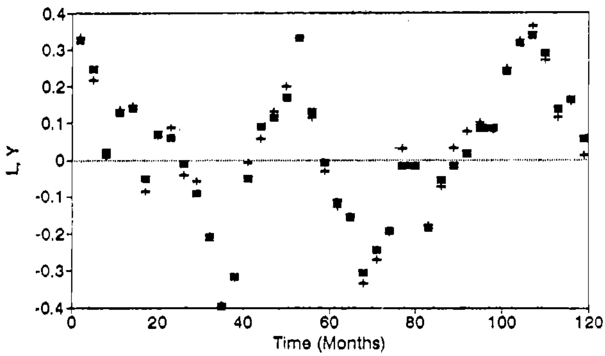


Figure 1c. Annual Data, K=.1

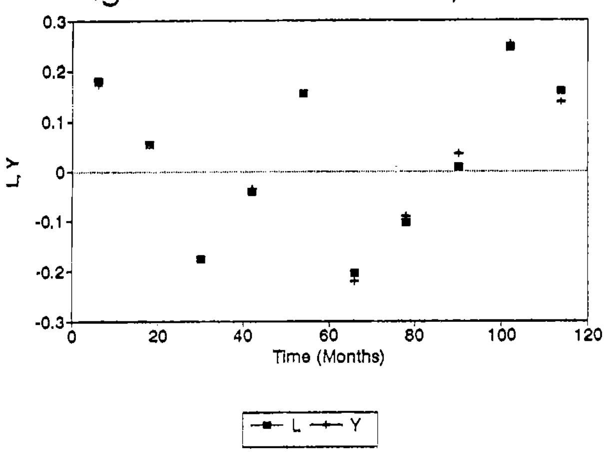


Figure 2a. Monthly Data, K=.2

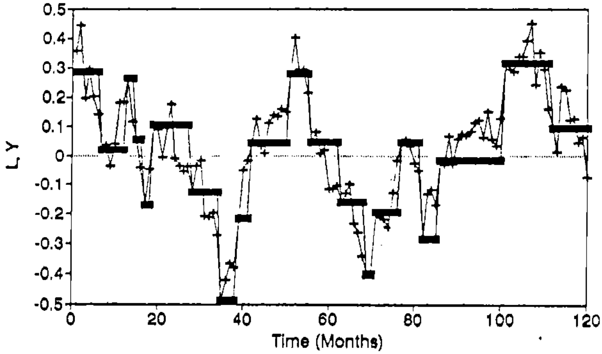


Figure 2b. Quarterly Data, K=.2

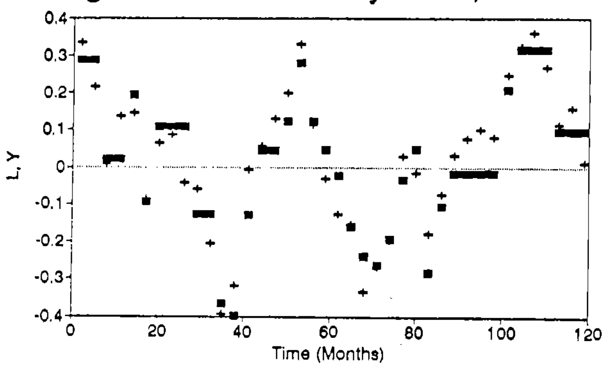
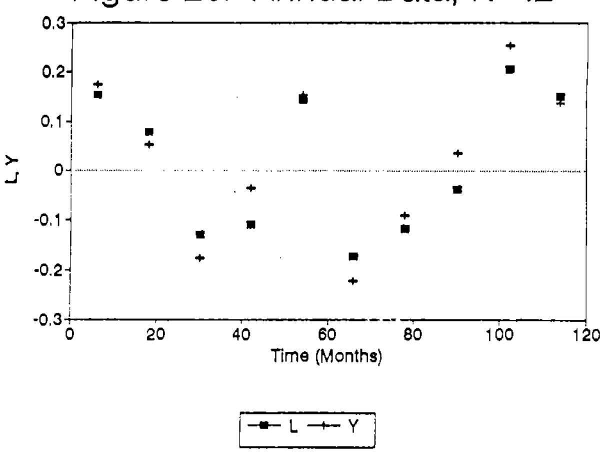


Figure 2c. Annual Data, K=.2



Though these calculations are suggestive, they define one very particular event (exact equality between adjacent observations on temporally aggregated data), and they are based on arbitrary constructions of sequences of L. To examine the issue further, consider simulations based on the modified version of (2):

(2') $$L_t = L_{t-1}, \text{ if } |L_{t-1} - Y_t| < K ,$$
$$L_t = Y_t, \text{ if } |L_{t-1} - Y_t| \geq K .$$

Let the monthly Y_t be generated by an AR(1) process with $\rho = .975$, with innovations distributed n(0, .01). This allows the simulation to reflect some cyclicality in the demand for labor. I calibrate the simulations to yield interesting values of p by choosing $K = \{.1, .2\}$.[4]

Ten years of monthly data from simulations based on the two values of K are shown in Figures 1a and 2a. (For these two simulations, p = .61 and .85 respectively.[5]) Especially in Figure 2a it is very clear that L does not change in response to small changes in product demand, but even in Figure 1a the rigidity in L is visible.

Figures 1b and 2b graph series on L and Y that are temporal aggregations of the monthly data to a quarterly basis, and Figures 1c and 2c aggregate the monthly data to create annual observations. While it is easy to infer something about the underlying temporally disaggregated structure from the quarterly data in Figure 2b, inferring anything other than smoothness from the quarterly data in Figure 1b is more difficult. Inferring anything other than smooth adjustment from the annual aggregates, even in Figure 2c, is impossible. At that level of temporal aggregation, and even though the underlying structure leads to substantial rigidity in labor demand, the data suggest only that that there is some indeterminacy in the relationship between L and Y.

The model in (2') is not forward-looking. Assuming for simplicity that Y is generated by an AR(1) process, an alternative is:

(2") $$L_t = L_{t-1}, \text{ if } \sum_{i=0}^{\infty} |L_{t-1} - \rho^i Y_t| / [1 + r]^i < K ,$$

$$L_t = L_t^*, \quad \text{if } \sum_{i=0}^{\infty} |L_{t-1} - \rho^i Y_t| / [1 + r]^i \geq K ,$$

where L^* solves $\min \{ \sum_{i=0}^{\infty} |L^* - \rho^i Y_t| / [1 + r]^i \}$.

A simulation of this model for a variety of assumptions about ρ, K and the variance of the innovations in Y did not alter the conclusions of the static model. Annual data show no evidence of having been generated by a monthly model like (2") unless K is relatively very large. As in the model based on static expectations, quarterly data yield the correct inference unless K is so small that discrete jumps in L occur very frequently.

In the monthly data in Hamermesh (1989) the mean of the estimated values of p was .8. The analysis in this Section makes it very clear that, even with this much rigidity, annual observations on microeconomic data will yield no evidence that the structure of adjustment costs is nonconvex. If the adjustment is not quite so rigid, quarterly data too will imply nothing is wrong with making the standard assumptions of convex adjustment costs. So long as we believe that employment decisions are made continuously, or at least monthly, microeconomic data aggregated to annual, or perhaps even to quarterly observations, will be of no use in allowing inferences to be made about the underlying structure of adjustment costs.

IV. Conclusions and Warnings

Barring assuming that adjustment costs are both quadratic and symmetric, we cannot use aggregated data to test any hypotheses or draw any inferences about the structure of adjustment costs. That is true for data aggregated across firms <u>and</u> for data that are aggregated temporally across the basic unit of time over which decisions are made. Only if we are interested in inferring how rapidly labor demand adjusts to shocks, and we do not care about the structure that generates the adjustment, are spatially and temporally aggregated data useful. Basing the underlying theoretical model on the firm's rational-expectations profit-maximizing path, or building a very complex error structure into the aggregate estimates, does not remove the inherent difficulty of aggregation. The aggregate estimates are useful only for forecasting the path of employment in the aggregate.

These conclusions contain an important warning. Obtaining large panels of annual data on firms is a useful step forward, as they allow us to circumvent any potential difficulties caused by heterogeneity of firms' behavior in nonlinear models of long-run employment determination. Similarly, estimating rational-expectations paths for factor demand using monthly or quarterly data on industries or larger aggregates is a major step in modeling how agents behave. But, if we wish to draw inferences about structure, we need to obtain micro data that are temporally disaggregated at least to quarterly observations. Without them estimates of dynamic labor demand can only offer smooth approximations to the underlying structures of adjustment costs.

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FOOTNOTES

1. Some of the basic studies in the employment-adjustment literature are Brechling (1965) and Nadiri and Rosen (1969). The leading work of the rational expectations genre is Sargent (1978).

2. These assumptions of independence are essential to derive the simple results for the three examples; but abandoning them does not vitiate the general result that one cannot infer either the structure of microeconomic adjustment from aggregate data. Also, in (2) and in the other examples I assume that employment is deterministic, given the structure of the shocks.

3. If we imagine a more complex process generating the Y_t, we can respecify (9') to include additional lags of the Y. Those respecifications, including up to 12 lags in the monthly data, 4 in the quarterly data, and 2 in the annual data, do not qualitatively change our conclusions from Table 2.

4. Choosing alternative values of ρ, σ^2 and K in no way alters the inferences in this Section.

5. The ten years of data shown in the Figures are the last ten years of simulations that set $Y_1 = 0$ and then run for 720 months. The results that are shown are thus essentially unaffected by any initial conditions.