Productivity As If Space Mattered: An Application to Factor Markets Across China

Wenya Cheng
LSE

John Morrow
Centre for Economic Performance, LSE

Kitjawat Tacharoen
Centre for Economic Performance, LSE

6 December 2012

Abstract

Optimal production decisions depend on local market characteristics. This paper develops a model to explain firm labor demand and firm density across regions. Firms vary in their technology to combine imperfectly substitutable worker types, and locate across regions with distinct distributions of workers and wages. Firm technologies which best match regional labor markets explain both productivity differences and firm density. Estimating structural model parameters is simple and relies on a two stage OLS procedure. The first stage estimates local market conditions using firm employment and regional data, while the second incorporates regional costs into production function estimation. The method is applied to Chinese manufacturing, population census and geographic data to estimate local market costs and production technologies. In line with the model, we find that labor markets which provide cost advantages explain substantial differences in firm productivity. Furthermore, regions which have lower optimal hiring costs attract more firms per capita.

JEL Codes: D22, D24, J24, J30, O15, R11.
Keywords: Structural Estimation, Productivity, Firm Location, China.

Acknowledgments. We thank Maria Bas, Sabine D'Costa, Fabrice Defever, Swati Dhingra, Ben Faber, Rebecca Lessem, Alan Manning, Monique Newiak, Emanuel Ornelas, Gianmarco Ottaviano, Dimitra Petropoulou, Veronica Rappoport, Tom Sampson, Daniel Sturm, Heiwai Tang and Greg Wright for insightful comments and especially Xiaoguang Chen. We also thank participants at the LSE Geography, Labor and Trade Workshops, Nordic Development, CSAEM and Warsaw School.

Corresponding Author: j.morrow1@lse.ac.uk

1 Introduction

A number of studies document large and persistent differences in productivity across both countries and firms.[1] However, these differences remain largely 'some sort of measure of our ignorance' (Abramovitz, 1956). This paper inquires to what extent the supply characteristics of regional input markets might help explain such systematic productivity dispersion across firms. It would be surprising if disparate factor markets result in similar outcomes, when clearly the prices and quality of inputs available vary considerably over space. Modeling firm adaptation to different factor markets provides deeper insights and testable predictions about how firms produce and where they choose to locate.

Differences between factor markets, especially for labor, are likely to be especially stark in developing economies undergoing urbanization (Lewis, 1954), or when government policies increase relocation costs beyond those normally present. Institutional mobility constraints, such as the *hukou* system in China, further exacerbate differences in the composition of labor markets. Even the US labor market, which is considered relatively fluid, exhibits high migration costs as measured by the wage differential required to drive relocation (Kennan and Walker, 2011). Thus, free movement of factors does not mean frictionless movement, and recent work has indicated imperfect factor mobility has sizable economic effects (Topalova, 2010). Rather than considering the forces which cause workers to locate across space, this paper instead takes a different turn to inquire what existing differences in regional input markets imply for firm input use, location and productivity.

To better understand these issues, we propose a multi-region, multi-industry general equilibrium model. Industries vary in team technology, i.e. their ability to substitute between different types of labor (e.g. Bowles, 1970). Each region is endowed with a different distribution of skill types and wages across workers. Firms freely locate and hire a team of workers by choosing the optimal combination of skill levels given local conditions. Since firms take regional characteristics as given, each firm chooses an optimal labor force conditional on industry technology and locality. It follows that the comparative suitability of regions varies by industry. Firms thus locate in proportion to the cost advantages available in each region.

In the model, firm hiring depends on the local distribution of worker types and wages. Since labor demand depends on model parameters and regional labor market conditions, this implies real labor costs vary by region and industry. These labor costs help explain

[1] See Syverson (2011) for a review.

differences in productivity.[2] However, it is not immediately clear that such productivity differences are of an economically large magnitude. To quantify real world supply conditions, we develop an estimation strategy for the key structural parameters. A simple relationship obtains between the firm-level shares of worker types hired and regional observables, which can be estimated by OLS as a first stage. The first stage identifies the labor technology parameters and allows computation of regional labor costs by industry, linking regional markets to productivity. Furthermore, the model relaxes the often imposed restriction that production be supermodular, a restriction that would otherwise often bind in our sample. The second stage incorporates regional costs into production function estimation, either by OLS or other commonly used methods. This strategy is straightforward to implement, and simulation of the underlying production model shows little accuracy is lost in comparison to full structural estimation.

The procedure just outlined is applied to manufacturing and population census data spread over three hundred prefectures in China. The manufacturing survey reports the distribution of workers across skills for each firm, while the population census provides regional distributions of wages and worker skill types. By revealing how firm demand for skills varies with local conditions, this information allows recovery of the unit costs for labor across China. Our estimates imply an interquartile difference in labor costs of 30 to 80 percent. As predicted by the model, labor costs are negatively related to the value added per capita across regions. This indicates that economic activity locates where regional costs are lowest.

A second stage estimates production function parameters, explicitly accounting for regional cost differences. Since firms are capable of substituting out of labor inputs when they are relatively expensive, this fact alters estimation of the relative share of labor in production. Once this effect is accounted for, labor cost differences result in firm productivity differences of 3 to 17 percent. The estimates show that favorable labor market conditions explain substantial differences in firm productivity. Once local market costs are controlled for, 'residual' productivity is a stronger predictor of firm performance characteristics such as survival and growth. This suggests that the unobservables which make firms more competitive are often conflated with advantageous input markets.

Related work. The importance of local market characteristics, especially in developing countries, has recently been emphasized by Karadi and Koren (2012). These authors calibrate a spatial firm model to sector level data in developing countries to better account for the role of firm location in measured productivity. Moretti (2011) reviews work on local

[2]Effective labor costs are driven by the complementarity of regional endowments with industry technology, and the paper refers to these additional real production possibilities as 'productivity'.

labor markets and agglomeration economies, explicitly modeling spatial equilibrium across labor markets. Distinct from this literature, we take the outcome of spatial labor markets as given and focus on the trade offs firms face and the consequences of regional markets in productivity measurement and firm location.

Several papers have explored how different aspects of labor affect firm-level productivity. There is substantial work on the effect of worker skills on productivity (Abowd Kramarz and Margolis (1999, 2005), Fox and Smeets (2011)).[3,4] In contrast, this paper considers the role of differences in input markets across regions.

Within the trade literature, a few studies propose that different industries perform optimally under different degrees of skill diversity. Based on this idea, Grossman and Maggi (2000) build a theoretical model explaining how differences in skill dispersion across countries could determine comparative advantage and global trade patterns. Building on this work, Morrow (2010) proposes a multi-industry model of firms which allows for technology choice and general skill distributions to estimate the model across developing countries, finding that skill diversity is significant in explaining productivity and export differences.

Although we are unaware of other studies estimating model primitives as a function of local market characteristics, reduced form empirical work is consonant with the theoretical implications. Iranzo, Schivardi, and Tosetti (2008) find that higher skill dispersion is associated with higher TFP in Italy. Similarly, Parrotta, Pozzoli, and Pytlikova (2011) find that diversity in education leads to higher productivity in Denmark. Martins (2008) finds that firm wage dispersion affects firm performance in Portugal. Bombardini, Gallipoli, and Pupato (2011) use literacy scores to show that countries with more dispersed skills specialize in industries characterized by lower skill complementarity. In contrast, this paper combines firm and population census data to explicitly model regional differences in input markets, leading to micro founded identification and estimates. The method used is novel, and results of this paper highlight the degree to which firm behavior are influenced by economic geography through the availability of inputs.[5]

Clearly this study also contributes to the empirical literature on Chinese productivity. Ma, Tang, and Zhang (2011) show that exporting is positively correlated with TFP and that

[3]Other labor characteristics that drive productivity include managerial talent and practices (Bloom and Reenen, 2007), social connections among workers (Bandiera, Barankay, and Rasul, 2009), organizational form (Garicano and Heaton, 2010) and incentive pay (Lazear, 2000).

[4]Other determinants of firm productivity include market structure (Syverson (2004)), product market rivalry and technology spillovers (Bloom, Schankerman, and Van Reenen (2007)) and vertical integration (Hortaçsu and Syverson (2007), Atalay, Hortacsu, and Syverson (2012)).

[5]The importance of backward linkages for firm behavior are a recurring theme in both the development and economic geography literature, see Hirschman (1958) and recently Overman and Puga (2010).

firms self select into exporting which, ex post, further increases TFP. Brandt et al. (2009) estimate Chinese firm TFP, showing that new entry accounts for two thirds of TFP growth and that TFP growth dominates input accumulation as a source of output growth. Hsieh and Klenow (2009) posit that India and China have lower productivity relative to the US due to resource misallocation and compute how manufacturing TFP in India and China would increase if resource allocation was similar to that of the US. This paper uncovers local factors that determine productivity. How this interacts with the above mechanisms is a potential area for further work.[6]

The rest of the paper continues by laying out a model that incorporates a rich view of the labor hiring process. The model explains how firms internalize local labor market conditions to maximize profits, resulting in an industry specific unit cost of labor by region. Section 3 places these firms in a general equilibrium, monopolistic competition framework, in particular addressing where firms locate. Section 4 explains how the model can be estimated with a simple nested OLS approach, and is illustrated using a simulated data set generated by the model. Section 5 discusses details of the data, while Section 6 presents our model estimates and uses them to explain the effect of different regional input markets on firm behavior. Section 7 concludes.

2 The Role of Skill Mix in Production

The primary goal of this section is to develop a model of firm hiring which takes into account both the wages and quantity of locally available worker types. Recently, both Borjas (2009) and Ottaviano and Peri (2010) have emphasized the importance of more complete model frameworks to estimate substitution between worker types. However, in distinction to most of the labor literature, our primary interest is firm behavior and accordingly we develop a model that predicts hiring by firms rather than wages to estimate substitution patterns.

The model specifies a theory of the firm which begins with a neoclassical production function combining homogeneous inputs (materials, capital) and differentiated inputs (types of labor). While homogeneous inputs are perfectly mobile within industries, labor is perfectly mobile within regions. Industries are assumed to have different technologies available for combining types of labor into teams. Since workers are imperfectly substitutable, they potentially induce spillovers within firms, a distinct possibility allowed for by our model, and

[6]Such regional differences might help explain the Chinese export facts of Manova and Zhang (2012) and the different impact of liberalization across trade regimes found by Bas and Strauss-Kahn (2012).

consequently are not paid their marginal product.[7] We proceed with a detailed specification of the labor hiring process, solving for firms' optimal responses to prevailing labor market supply conditions. This provides a characterization of the unit cost for labor by region which depends on local conditions and firm technology. This induces comparative advantage across regions for any given technology, and thereby helps explain productivity differences in terms of local input markets.

2.1 Firm Production

Firm j within an industry T faces a neoclassical production technology $F_j^T(M,K,L)$ which combines materials M, capital K and labor L to produce output. While M and K are composed of homogeneous units measured by value, labor is composed of a heterogeneous team of workers who provide an aggregate vector of human capital H. An industry specific capital stock K^T is mobile within each industry, and in equilibrium is available at rental rate r_K^T. Similarly, an industry specific stock of materials M^T is mobile and available at a price r_M^T.

Labor is intersectorally mobile but interregionally immobile, and consists of $\mathbb{S}$ skill types of workers, indexed $i \in \{1,\dots,\mathbb{S}\}$, who are combined to provide effective labor L. The amount of L produced by the firm depends on the composition of a team through a technological parameter θ^T in the following way:

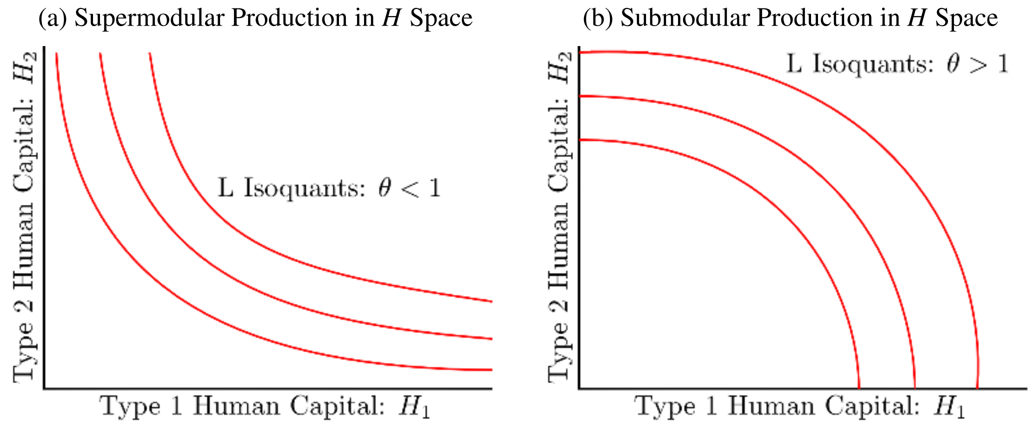
$$L \equiv \left(H_1^{\theta^T} + H_2^{\theta^T} + \ldots + H_{\mathbb{S}}^{\theta^T}\right)^{1/\theta^T}. \tag{2.1}$$

Notice that in the case of $\theta^T = 1$, this specification collapses to a model where L is the total level of human capital $H_{\text{TOT}} = \sum_i H_i$. More generally, the Marginal Rate of Technical Substitution of type i for type i' is $(H_i/H_{i'})^{\theta^T-1}$. $\theta^T < 1$ implies worker types are complementary, so that the firm's ideal workforce tends to represent a mix of all types (Figure 2.1a). In contrast, for $\theta^T > 1$, firms are more dependent on singular sources of human capital as L becomes submodular, i.e. convex in the input of each single type (Figure 2.1b).[8] We will specify a hiring process so that despite the convexity inherent in Figure 2.1b, once firms choose the quality of their workers through hiring standards $\underline{h}$, the labor isoquants resume their typical shapes as in Figure 2.2. This avoids the possibility that some worker types are never hired, in line with expectations about real world data patterns.

[7] Such spillovers are internalized by firms in the model. The extent to which spillovers might also occur across industries is beyond the scope of this study, however see Moretti (2004) for evidence in the US context.

[8] See Morrow (2010) for a more detailed interpretation of super- and sub-modularity and implications.

Figure 2.1: Human Capital Isoquants



Rewriting Equation (2.1) in terms of human capital shares within the firm shows the labor provided per unit of human capital is

$$L/H_{\mathrm{TOT}} = \left((H_1/H_{\mathrm{TOT}})^{\theta^T} + (H_2/H_{\mathrm{TOT}})^{\theta^T} + \ldots + (H_{\mathbb{S}}/H_{\mathrm{TOT}})^{\theta^T}\right)^{1/\theta^T}.$$

Writing the shares of human capital across types of workers as $\tilde{H} \equiv (H_1/H_{\mathrm{TOT}}, \ldots, H_{\mathbb{S}}/H_{\mathrm{TOT}})$, effective labor can be written

$$\underbrace{L}_{\text{Effective Labor}} = \underbrace{\phi\left(\tilde{H}, \theta^T\right)}_{\text{Team Productivity Effect}} \cdot \underbrace{H_{\mathrm{TOT}}}_{\text{Total Human Capital}}$$

where $\phi\left(x, \theta^T\right) \equiv \left(\sum_i x_i^{\theta^T}\right)^{1/\theta^T}$ so that the output is given by $F_T\left(M, K, \phi\left(\tilde{H}, \theta^T\right) \cdot H_{\mathrm{TOT}}\right)$.

Although the technology θ^T is the same for all firms in an industry, firms do not all face the same regional factor markets. Explicitly modeling these disparate markets emphasizes the role of regional heterogeneity in supplying human capital inputs to the firm in terms of both price and quality. This provides not only differences in productivity across regions by technology, but since industries differ in technology, local market conditions are more or less amenable to particular industries. We now detail the hiring process, introducing different markets and deriving firms' optimal hiring to best accommodate these differences.

2.2 Optimal Hiring by Region and Technology

In each region R, workers command region specific wages for each type of labor $w_R = \left(w_{R,1},\ldots,w_{R,\mathbb{S}}\right)$ and have type-industry specific human capital $\underline{m}^T = \left(\underline{m}_1^T,\ldots,\underline{m}_{\mathbb{S}}^T\right)$. In order to hire workers, a firm must pay a fixed search cost of f effective labor units, at which point a distribution of worker types with regional frequencies $a_R = \left(a_{R,1},\ldots,a_{R,\mathbb{S}}\right)$ are available from the search process.[9] Each worker has a firm specific match quality $h \sim \Psi$ which is observed during search and the firm hires on the basis of match quality. Consequently, the firm chooses a minimum threshold of match quality for each type they will retain, $\underline{h} = (\underline{h}_1,\ldots,\underline{h}_{\mathbb{S}})$.[10] Upon keeping a preferred set of workers, the firm may repeat this process N times until achieving their desired workforce. At the end of hiring, the amount of human capital produced by each type i is given by

$$H_i \equiv N \cdot a_{R,i}\underline{m}_i^T \int_{\underline{h}_i}^{\infty} h d\Psi. \tag{2.2}$$

From a firm's perspective, the threshold of worker match quality $\underline{h}$ is a means to choose an optimal level of H, holding N fixed. However, as a firm lowers its quality threshold, it faces an increasing average cost of each type of human capital H_i . These increasing average costs induce the firm to maintain a positive match quality threshold and to search repeatedly for suitable workers.

The total costs of hiring labor depend on the regional wage rates w_R, the availability of workers a_R, and the unit cost of labor in region R using technology T, labeled c_R^T. Since the total number of each type i hired is $Na_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)$, the total hiring bill is

$$\text{Total Hiring Costs}: \quad N\left[\sum_i w_{R,i}a_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)+fc_R^T\right]. \tag{2.3}$$

Clearly, the firm faces a trade-off between the quantity and quality of workers hired. For instance, the firm might hire a large number of workers and "cherry pick" the best matches by choosing high values for $\underline{h}$ or save on interviewing costs f by choosing a low number of prospectives N and permissively low values for $\underline{h}$. This trade off and its dependence

[9] The weights a_R can capture both the frequencies of available workers in addition to the possibility that certain types of workers may be more difficult to hire for a particular task.

[10] This assumption is familiar from labor search models. We do not explicitly model equilibrium unemployment due to the lack of a simple form for cross regional empirical work (see Helpman, Itskhoki, and Redding (2010)). Unlikely Helpman, et al. differences in hiring patterns across firms within the same industry are determined by regional market conditions, rather than a productivity draw.

on the regional labor supply characteristics a_R and w_R is made explicit by considering the technology and region specific cost function $C_T\left(H|a_R,w_R\right)$, defined by

$$C_T \equiv \min_{N,\underline{h}} N\left[\sum_i a_{R,i}w_{R,i}\left(1-\Psi\left(\underline{h}_i\right)\right)+fc_R^T\right] \text{ where } H_i \leq Na_{R,i}\underline{m}_i^T\int_{\underline{h}_i}^{\infty} hd\Psi. \tag{2.4}$$

Letting μ_i denote the Lagrange multiplier for each of the $\mathbb{S}$ cost minimization constraints, the first order conditions for $\{\underline{h}_i\}$ imply $\mu_i = w_{R,i}/\underline{m}_i^T\,\underline{h}_i$, while the condition for N implies

$$C_T\left(H|a_R,w_R\right) = \sum_i \mu_i H_i = \sum w_{R,i}H_i/\underline{m}_i^T\,\underline{h}_i. \tag{2.5}$$

Equation (2.5) shows that the multipliers μ_i are the marginal cost contribution (per skill unit) to H_i of the last type i worker hired.

The trade off between being more selective (high $\underline{h}$) and avoiding search costs (fc_R^T) is clearly illustrated by combining Equations (2.3) and (2.5), which shows:

$$\sum_i a_{R,i}w_{R,i}\int_{\underline{h}_i}^{\infty}\left(h-\underline{h}_i\right)/\underline{h}_i d\Psi = fc_R^T. \tag{2.6}$$

The LHS of Equation (2.6) decreases in $\underline{h}$, so when a firm faces lower interviewing costs it can afford to be more selective by increasing $\underline{h}$. Conversely, in the presence of high interviewing costs, the firm optimally "lowers their standards" $\underline{h}$ to increase the size of their workforce without interviewing additional workers.

2.3 Cost Minimization

For a firm j to produce Q_j units of output at minimal cost, inputs are chosen to solve

$$\min_{K,M,H} C_T\left(H|a_R,w_R\right)+r_K^T K+r_M^T M \text{ subject to } F_j^T\left(M,K,\phi\left(\tilde{H},\theta^T\right)\cdot H_{\text{TOT}}\right) \geq Q_j. \tag{2.7}$$

The first order conditions for H_{TOT} and H_i immediately imply that

$$\left(w_{R,i}H_i/\underline{m}_i^T\,\underline{h}_i\right)/C_T\left(H|a_R,w_R\right) = d\ln L/d\ln H_i = \left(\tilde{H}_i + d\ln\phi\left(\tilde{H},\theta^T\right)/d\ln H_i\right). \tag{2.8}$$

This fixes a key relationship about the *wage premium*, defined as the share of wages paid to a type beyond the share of human capital contributed. From (2.8), let

$$\widetilde{w}^T_{R,i} \equiv \left(w_{R,i} H_i / \underline{m}^T_i \underline{h}_i\right) / C_T \left(H | a_R, w_R\right)$$

denote the share of wages attributable to workers of type i. Then from (2.8) we have:

$$\text{Wage Premium}: \quad \underbrace{\widetilde{w}^T_{R,i} - \tilde{H}_i}_{\text{Share of Cost} - \text{Share of Human Capital}} = \underbrace{d \ln \phi \left(\tilde{H}, \theta^T\right) / d \ln H_i}_{\text{Productivity Elasticity}}. \tag{2.9}$$

Explicitly, $d \ln \phi \left(\tilde{H}, \theta^T\right) / d \ln H_i = \tilde{H}_i^{\theta^T} / \sum_z \tilde{H}_z^{\theta^T} - \tilde{H}_i$, so that $\widetilde{w}^T_{R,i} = \tilde{H}_i^{\theta^T} / \sum_j \tilde{H}_j^{\theta^T}$. Notably, when labor types are perfectly substitutable ($\theta^T = 1$), $\phi \left(\tilde{H}, \theta^T\right)$ is identically 1 so the wage premium is zero for all types.

2.4 Unit Labor Costs under Pareto Match Quality

The above reasoning shows the relationship between technology and the optimal choice of worker types. To make this model more concrete, we assume that firm specific match quality follows a Pareto distribution $\Psi(h) \equiv 1 - h^{-k}$. Here k is the shape parameter and 1 is the minimum value h can take. Under a Pareto distribution, a sufficient condition for a firm to optimally hire every type of worker is that

$$\beta^T \equiv \theta^T + k - k\theta^T > 0.$$

We now prove this result, stated as

Proposition 1. *If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers.*

Proof. Let c^T_R denote a firm's unit labor cost when all worker types are hired, and $\check{c}^T_R$ the unit labor cost if a subset of types $\mathbb{T} \subset \{1, \dots \mathbb{S}\}$ is hired. For the result, we require that $c^T_R \leq \check{c}^T_R$ for all $\mathbb{T}$. Considering a firm's cost minimization problem when $\mathbb{T}$ are the only types available shows with Equation (2.10) that

$$\check{c}^T_R = \left[\sum_{i \in \mathbb{T}} \left[a_{R,i} \left(\underline{m}^T_i\right)^k w^{1-k}_{R,i} / f(k-1)\right]^{\theta^T / \beta^T}\right]^{\left(\beta^T / \theta^T\right)/(1-k)}.$$

Considering then that

$$c_R^T/\check{c}_R^T = \left[1+\left(\sum_{i\notin\mathbb{T}}\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}\right]^{\theta^T/\beta^T} / \sum_{i\in\mathbb{T}}\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}\right]^{\theta^T/\beta^T}\right)\right]^{\left(\beta^T/\theta^T\right)/(1-k)},$$

clearly $c_R^T \leq \check{c}_R^T$ so long as $\beta^T/\theta^T\,(1-k) \leq 0$, which holds for $\beta^T > 0$ since $k > 1$. □

A positive β^T is guaranteed by a supermodular labor technology ($\theta^T < 1$). For submodular production ($\theta^T > 1$), a positive β^T is a requirement that the Pareto shape parameter k be sufficiently close to 1. This guarantees the tail of the match quality distribution is thick enough to justify hiring at least a few workers of each type. This induces the isoquants depicted in Figure 2.2, which illustrates a more standard trade off between different types of workers, so long as the coordinates are transformed to the space of hiring standards $\underline{h}$.

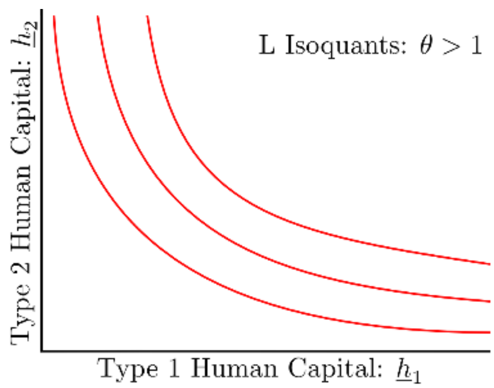


Figure 2.2: Submodular Production in $\underline{h}$ Space

The general cost function derived implies the unit labor cost of L in region R is

$$\text{Unit Labor Cost Problem}: \quad c_R^T \equiv \min_H C_T\left(H|a_R, w_R\right) \text{ subject to } L = \phi\left(\tilde{H},\theta^T\right)\cdot H_{\text{TOT}} = 1.$$

From Equations (2.5) and (2.9) the unit labor cost function may be solved as

$$\text{Unit Labor Costs}: \quad c_R^T = \left[\sum_i \left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}/f\,(k-1)\right]^{\theta^T/\beta^T}\right]^{\left(\beta^T/\theta^T\right)/(1-k)}. \qquad (2.10)$$

Notably, the number of times a firm goes to hire workers, N, can be solved as $N = 1/fk$. Thus, N is decreasing in both the cost of hiring and k, as increases in k imply a thinner right tail of match quality, so that repeatedly screening workers has lower returns. Finally, $\widetilde{w}_{R,i}^T$, the share of wages attributable to workers of type i becomes

$$\widetilde{w}_{R,i}^{T} = \left(a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k}\right)^{\theta^T/\beta^T} / \sum_j \left(a_{R,j}\left(\underline{m}_j^T\right)^k w_{R,j}^{1-k}\right)^{\theta^T/\beta^T}$$

Equation (2.10) summarizes the cost of one unit of labor L in terms of the Pareto shape parameter k, the technology θ^T and regional characteristics a_R and w_R. Such differences in regional unit labor costs translate directly into measured productivity differences across firms. In order to solve for total unit costs (which include non-labor costs), we assume each production function F_j^T is defined by the following Cobb-Douglas form:

$$F_j^T(M,K,L) = \eta_j^{-1} \cdot M^{\alpha_M^T} K^{\alpha_K^T} L^{\alpha_L^T}. \tag{2.11}$$

Here η_j is a Hicks neutral cost shifter which varies across firms, and we assume constant returns to scale. It is then straightforward to derive total unit costs from (2.7) and (2.10) as

$$\text{Total Unit Costs :} \quad u_{Rj}^T = u_R^T \eta_j = \left(r_M^T/\alpha_M^T\right)^{\alpha_M^T} \left(r_K^T/\alpha_K^T\right)^{\alpha_K^T} \left(c_R^T/\alpha_L^T\right)^{\alpha_L^T} \cdot \eta_j, \tag{2.12}$$

where u_R^T represents the regional component of unit costs not idiosyncratic to firms.

Section 4 presents a two stage OLS procedure which can recover the differences in unit labor costs $c_R^T(a_R, w_R)/c_{R'}^T(a_{R'}, w_{R'})$ between any two regions R and R', but first we resolve firm behavior in general equilibrium.

3 Firm Production under Monopolistic Competition

This section combines the insights into firm behavior just developed into a general equilibrium model of monopolistic competition. Firms, who are ex ante identical, choose among regions to locate. Key to a firm's location decision are the expected profits of entry. These profits depend on 1) the distribution of worker types and wages and 2) the level of competition present from other firms who enter the region. We determine equilibrium production and location choices conditional on wages, which provides the relationship of regional costs to firm density. We also show an equilibrium wage vector exists which supports these choices by firms.

3.1 Model Setting

Each region R is endowed with a population $\mathbb{P}_R$ of workers composed of $\mathbb{S}$ types. We take the well known approach of Melitz (2003) to model firms who face fixed entry costs F_e, receive a random cost draw $\eta_j \sim G$ and face a fixed production cost f_e.[11] Akin to Bernard, Redding, and Schott (2007), firms combine different types of inputs to produce. Distinct from both these models, firms ex ante may freely enter any region R which will determine the cost structure they face. Each firm j produces a distinct variety, and in equilibrium a mass of firms $\mathbb{M}_R^T$ enter and entrants with cost draws less than a prohibitively high cost level $\overline{\eta}_R^T$ produce. $\mathbb{M}_R^T$ and $\overline{\eta}_R^T$ together determine the set of varieties available to consumers.

3.2 Aggregate Income, Demand and Budget Shares

Consumption is determined by the aggregate level of income I_{Agg}, and since labor is supplied inelastically, this is necessarily

$$I_{\text{Agg}} = \sum_R \sum_i \underbrace{w_{R,i} a_{R,i} \mathbb{P}_R}_{\text{Total Wages of Type i in R}} + \sum_T \underbrace{r_M^T M^T + r_K^T K^T}_{\text{Non-labor Income}}. \tag{3.1}$$

Consumer preferences over varieties j and quantities $\left\{Q_{Rj}^T\right\}$ take the Dixit-Stiglitz form

$$U_R^T \equiv U\left(\mathbb{M}_R^T, \overline{\eta}_R^T, Q_R^T\right) = \mathbb{M}_R^T \int_0^{\overline{\eta}_R^T} \left(Q_{Rj}^T\right)^\rho dG(j)$$

in each region and industry, with total utility $U(\mathbb{M}, \overline{\eta}, Q) \equiv \Pi_T \Pi_R \left(U_R^T\right)^{\sigma_R^T}$, where σ_R^T are relative weights put on final goods normalized so that $\sum_{T,R} \sigma_R^T = 1$.

Firms are the sole sellers of their variety, and thus are monopolists who provide their variety at a price P_{Rj}^T. Consumers, in turn, face a vector of prices $\left\{P_{Rj}^T\right\}$, and a particular consumer with income I has the following demand curve for each variety:

$$Q_{Rj}^T = I \cdot \left(P_{Rj}^T U_R^T / \sigma_R^T\right)^{\frac{1}{\rho-1}} / \sum_{t,r} \left(\sigma_r^t\right)^{\frac{1}{\rho-1}} \mathbb{M}_r^t \int_0^{\overline{\eta}_r^t} \left(\left(P_{r,z}^t\right)^\rho U_r^t\right)^{\frac{1}{\rho-1}} dG(z). \tag{3.2}$$

Clearly, even if consumers have different incomes, aggregate demand for variety j corresponds to that of a representative consumer with income equal to aggregate income, I_{Agg}.

[11] G is assumed to be absolutely continuous with finite mean.

After paying an entry cost of F_e output units, firms know their cost draw, which paired with regional input markets determine their total unit cost u_{Rj}^T. Firms maximize profits

$$\pi_{Rj}^T\left(P_{Rj}^T\right) = \left(P_{Rj}^T - u_{Rj}^T\right) Q_{Rj}^T - u_R^T f_e$$

by choosing an optimal price $P_{Rj}^T = u_{Rj}^T/\rho$, resulting in a markup of $1/\rho$ over costs. Firms who cannot make a positive profit do not produce to avoid paying the fixed cost of f_e output units. Since profits decrease in costs, there is a unique cutoff cost draw $\overline{\eta}_R^T$ which implies zero profits, while firms with $\eta_j < \overline{\eta}_R^T$ produce. As there are no barriers to entry besides the entry cost F_e, firms enter in every region until expected profits are zero. This yields the

$$\text{Spatial Zero Profit Condition :} \quad \mathrm{E}\left[\pi_{Rj}^T\right] = F_e, \quad \forall R, T.$$

The expressions which fix the cutoff cost draw $\overline{\eta}_R^T$ and mass of entry $\mathbb{M}_R^T$ can be neatly summarized by defining the mass of entrants who produce, $\widetilde{\mathbb{M}}_R^T$, and the (locally weighted) average cost draw in each region, $\widetilde{\eta}_R^T$:

$$\widetilde{\mathbb{M}}_R^T \equiv \mathbb{M}_R^T G\left(\overline{\eta}_R^T\right), \qquad \widetilde{\eta}_R^T \equiv \int_0^{\overline{\eta}_R^T} \left(\eta_{Rz}^T u_R^T \left(U_R^T\right)^{1/\rho}\right)^{\rho/(\rho-1)} dG(z)/G\left(\overline{\eta}_R^T\right).$$

It is shown in the Appendix that $\overline{\eta}_R^T$ depends only on f_e, F_e, and G, so there is a unique cutoff cost $\overline{\eta} = \overline{\eta}_R^T$ across all regions and industries. The appendix also shows that the free entry and zero profit conditions imply that the share of income spent on goods from each region and technology pair (R,T) is given by

$$\text{Consumer Budget Share for R, T :} \quad \mathbb{M}_R^T u_R^T / \sum_{t,r} \mathbb{M}_r^t u_t^t = \sigma_R^T / \sum_{t,r} \sigma_r^t = \sigma_R^T.$$

Having determined firm behavior in the product market, we now examine input markets.

3.3 Regional Factor Market Clearing

The only remaining equilibrium conditions are that input prices guarantee firm input demand exhausts material and capital stocks, in addition to each regional pool of workers. A final assumption on the budget shares $\left\{\sigma_R^T\right\}$ ensures that two regions which have identical skill distributions have the same wage schedule. Within an industry, each σ_R^T is proportional to $\mathbb{P}_R$, so that $\sigma_R^T = \sigma^T \mathbb{P}_R$ for some σ^T. Since production is Cobb-Douglas, the share of total costs (equal to I_{Agg}) which go to each factor is the factor output elasticity, so full resource utilization of materials and capital requires

$$M^T = \alpha_M^T \sigma^T I_{\text{Agg}} \mathbb{P} / r_M^T, \qquad K^T = \alpha_K^T \sigma^T I_{\text{Agg}} \mathbb{P} / r_K^T. \tag{3.3}$$

where $\mathbb{P} \equiv \sum_R \mathbb{P}_R$ is the total population. These two equations capture the allocation of technology specific resources across regions.

In contrast, labor is immobile outside of a region, and effective labor of L_R^T is produced by each technology in each region. Since the wage bill $L_R^T c_R^T$ must receive a share α_L^T of total revenues,

$$\text{Aggregate Labor Demand}: \quad L_R^T = \alpha_L^T \sigma^T I_{\text{Agg}} \mathbb{P}_R / c_R^T. \tag{3.4}$$

Embedded in each L_R^T is the set of workers hired by firms attendant to regional market conditions. The number of workers of type i employed with technology T in region R is labeled $e_{R,i}^T$. The Pareto match assumption and firm hiring conditions imply $e_{R,i}^T$ takes the form[12]

$$e_{R,i}^T = a_{R,i}^{\theta^T/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} L_R^T \left(c_R^T\right)^{k/\beta^T} \left(f\left(k-1\right)\right)^{-\theta^T/\beta^T}. \tag{3.5}$$

The total demand for employees of each type in a region R, $\sum_T e_{R,i}^T$, must equal the supply of $a_{R,i}\mathbb{P}_R$, yielding the regional resource clearing conditions. Wages are determined by

$$a_{R,i} = \sum_T e_{R,i}^T / \mathbb{P}_R = w_{R,i}^{-1} \sum_t \sigma^t \alpha_L^t \widetilde{w}_{R,i}^t I_{\text{Agg}}, \quad \forall R, i. \tag{3.6}$$

Equation (3.6) affords a interpretation of equilibrium wages. A type i's contribution to mean wages, $a_{R,i} w_{R,i}$, is an average of the income spent on labor in an industry, times the wages attributable to each type:

$$a_{R,i} w_{R,i} = \sum_t \underbrace{\sigma^t}_{\text{Industry Share Per Capita}} \cdot \underbrace{\alpha_L^t}_{\text{Labor Share}} \cdot \underbrace{\widetilde{w}_{R,i}^t}_{\text{Type Share}} \cdot I_{\text{Agg}}$$

Solving Equation (3.6) requires finding a wage for each worker type in each region that fully employs all workers. Accordingly, showing that an equilibrium wage vector exists is slightly tricky. In order to do so, first note that the resource clearing conditions determine wages, provided an exogenous vector of unit labor costs $\left\{c_R^T\right\}$, as proved in the Appendix:

[12] See Supplemental Appendix.

Lemma. *There is a wage function $\mathbb{W}$ that uniquely solves (3.6) given unit labor costs.*

Of course, unit labor costs are not exogenous as in the Lemma, but rather depend on endogenous wages $\{w_{R,i}\}$. However, the lemma does show that the following mapping:

$$\{w_{R,i}\} \underset{\text{Equation } 2.10}{\mapsto} \left\{c_R^T\left(\{w_{R,i}\}\right)\right\} \underset{\text{Lemma}}{\mapsto} \mathbb{W}\left(\left\{c_R^T\left(\{w_{R,i}\}\right)\right\}\right),$$

which starts at one wage vector $\{w_{R,i}\}$ and ends at another wage vector $\mathbb{W}$ is well defined. This mapping is shown in the Appendix to have a fixed point, which yields[13]

Proposition 2. *An equilibrium wage vector exists which clears each regional labor market.*

3.4 Relative Concentration of Firms

Of course, differences in input costs will influence the relative concentration of firms across regions. Since regions may vary substantially in population size $\mathbb{P}$, the most relevant metric is the number of firms per capita in a region, $\widetilde{\mathbb{M}}_R^T/\mathbb{P}_R$. The number of firms per capita vary by both regional costs and the budget shares spent on goods from each industry. The impact of different regional costs can be clearly seen by fixing an industry T and considering the ratio of firms per capita in region R versus R' as in Equation (3.7):

$$\text{Firms per Capita, R to R}' : \quad \left(\widetilde{\mathbb{M}}_R^T/\mathbb{P}_R\right)/\left(\widetilde{\mathbb{M}}_{R'}^T/\mathbb{P}_{R'}\right) = u_{R'}^T/u_R^T = \left(c_{R'}^T/c_R^T\right)^{\alpha_L^T} \tag{3.7}$$

Equation (3.7) shows that areas with lower unit labor costs have more firms per capita. Additionally, the larger the share of labor in production, α_L^T, the more important are differences between regions. This relationship is summarized as

Proposition 3. *Within an industry, regions with lower labor costs have more firms per capita.*

The next section lays out a strategy to structurally estimate model parameters.

4 Estimation Strategy

This section lays out a simple two stage estimator to recover the underlying structural model parameters above. The estimator involves two regressions, with an intervening computation

[13] Factor price equalization does not generally hold across labor types since trade in goods is not a substitute for trade in factors. See the Appendix for some limited ways in which equalization does hold.

which can be done easily in most statistical software. The first stage equation determines firm labor demand, and unlike many approaches is based on the firm-level shares of workers hired across regions, rather than wages. The second stage equation uses regional unit labor costs fixed by the model and first stage to estimate the remaining parameters of the production function. To illustrate feasibility, we simulate a data set consistent with the firm production problem above and show our estimation method recovers model primitives accurately.

4.1 First Stage Estimation

The employment expression (3.5) determines the share of each type of workers hired in each region R and industry T. Since this does not vary by firm for fixed R and T, it follows that the share of workers of type i hired by firm j in R and T, $s^T_{R,ij}$, satisfies

$$\ln s^T_{R,ij} = -\frac{k}{\beta^T}\ln w_{R,i} + \frac{\theta^T}{\beta^T}\ln a_{R,i} + \frac{\theta^T}{\beta^T} k \ln \underline{m}^T_i + \frac{\theta^T}{\beta^T}\ln\frac{\left(\tilde{c}^T_R\right)^k}{f\,(k-1)} + \varepsilon_{ij}, \tag{4.1}$$

where ε_{ij} denotes a firm-type level error term and $\tilde{c}^T_R$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$[14]. To estimate this equation we use a combination of type and region dummies.[15] To further explain how regional variation identifies the model we discuss equilibrium hiring predicted by Equation (4.1) in Appendix E.2.

In order to control for firm characteristics which might influence hiring patterns across worker types, $\underline{m}^T_i$ is allowed to vary with firm observables labeled Controls_j:

$$\underline{m}^T_{ij} \equiv \underline{m}^T_i \cdot \exp\left\{\text{Controls}_j \gamma^T_i\right\}, \tag{4.2}$$

where γ^T_i is a type-industry specific estimate of characteristics which might influence the value of each worker type in an industry. The inclusion of Controls_j makes type specific human capital vary by firm, and accordingly we denote unit labor costs as c^T_{Rj}. We now discuss how the first stage estimates are used to estimate production function parameters in a second stage.

[14]Formally $\tilde{c}^T_R \equiv \min_H C_T\left(H|a_R, \left\{w_{R,i}^{-k/\theta^T(1-k)}\right\}\right)$ subject to $L = \phi\left(\tilde{H}, \theta^T\right)\cdot H_{\text{TOT}} = 1$.

[15]We suggest the convention of creating of type and region fixed effects, omitting the highest type fixed effect. The remaining type coefficients then correspond to the estimates of $\left(\theta^T/\beta^T\right) k \ln \underline{m}^T_i / \underline{m}^T_{\mathbb{S}}$.

4.2 Second Stage Estimation

From above we can estimate $\theta^T, k, \{\underline{m}_i^T/\underline{m}_{\mathbb{S}}^T\}, \{\gamma_i^T\}$ and therefore can estimate regional differences in unit labor cost functions, $\Delta \ln c_R^T \equiv \mathrm{E}\left[\ln c_{Rj}^T | R, T, \text{Controls}_j\right] - \mathrm{E}\left[\ln c_{Rj}^T | T\right]$. From above, revenues $P_{Rj}^T Q_{Rj}^T$ for a firm j satisfy

$$\ln P_{Rj}^T Q_{Rj}^T = \alpha_M^T \ln M_j + \alpha_K^T \ln K_j + \alpha_L^T \ln L_j - \ln \rho \eta_j. \tag{4.3}$$

As firm expenditure on labor $L \cdot c_{Rj}^T$ equals the share α_L^T of revenues $P_{Rj}^T Q_{Rj}^T$, we have $L_j c_{Rj}^T = \alpha_L^T P_{Rj}^T Q_{Rj}^T$ and taking differences with the population mean gives

$$\Delta \ln L_j = \Delta \ln P_{Rj}^T Q_{Rj}^T - \Delta \ln c_{Rj}^T. \tag{4.4}$$

Taking differences of Equation (4.3) with the population mean and using (4.4) yields

$$\Delta \ln P_{Rj}^T Q_{Rj}^T = \alpha_M^T \Delta \ln M_j + \alpha_K^T \Delta \ln K_j + \alpha_L^T \Delta \ln P_{Rj}^T Q_{Rj}^T - \alpha_L^T \Delta \ln c_{Rj}^T - \Delta \ln \eta_j.$$

So reduction gives the estimating equation

$$\Delta \ln P_{Rj}^T Q_{Rj}^T = \frac{\alpha_M^T}{1-\alpha_L^T} \Delta \ln M_j + \frac{\alpha_K^T}{1-\alpha_L^T} \Delta \ln K_j - \frac{\alpha_L^T}{1-\alpha_L^T} \Delta \ln c_{Rj}^T - \frac{1}{1-\alpha_L^T} \Delta \ln \eta_j. \tag{4.5}$$

The entire estimation procedure is now briefly recapped.

4.3 Estimation Procedure Summary

1. Using $s_{R,ij}^T$, the share of workers of type i hired in region R and industry T, estimate Equation (4.1), using type and region dummies.
2. Recover $\widehat{\theta^T}$, $\widehat{k}$, $\left\{\widehat{\underline{m}_i^T/\underline{m}_{\mathbb{S}}^T}\right\}$ and $\left\{\widehat{\gamma_i^T}\right\}$. Bootstrap standard errors or use the delta method.
3. Use Equation (2.10) to calculate estimates $\widehat{\Delta \ln c_{Rj}^T}$ by region and industry using the regional data $\{a_R\}$, $\{w_R\}$ and estimated $\widehat{\theta^T}$, $\widehat{k}$, $\left\{\widehat{\underline{m}_i^T/\underline{m}_{\mathbb{S}}^T}\right\}$ and $\left\{\widehat{\gamma_i^T}\right\}$ from Step 1.
4. Estimate Equation (4.5) using $\widehat{\Delta \ln c_{Rj}^T}$.

This specification is structural, but obviously does not compute every element of the model, and therefore efficiency of the estimator might suffer. In the Appendix, we both illustrate the estimator and evaluate efficiency loss by simulating firms which obey the production model specified above and apply these steps. In the simulation, the first stage can explain 99% of the variation in firm hiring of the full model and the second stage explains 97% of the variation in firm output, suggesting that the time savings of this specification likely outweigh any gain in estimation accuracy within the context of the model.

Having laid out both a production model detailing the interaction of firm technologies with local market conditions and specifying an estimation strategy, we now move on to applying the method to China using manufacturing and population census data. The next section discusses this data in detail while the sequel presents our results.

5 Data

This section discusses the data, in particular regional educational attainment and wages.

5.1 Data Overview

Our firm level data comes from the 2004 Survey of Industrial Firms conducted by the Chinese National Bureau of Statistics. It includes all enterprises with sales over 5 million RMB. The data includes firm's ownership, location, industry, financial variables, profit and cash flow statements. Firms report their number of employees by education level, in addition to output, value added sales and export value. For detailed summary statistics regarding these firms and industrial characteristics see Appendix C.3. From the Survey, a subsample was constructed of manufacturing firms who report positive net fixed assets, material inputs, output, value added and wages. Firms with fewer than 8 employees were excluded as they fall in a different legal regime. The final sample includes 141,464 firms in 284 prefectures and 19 industries at the two digit level.

Firm capital stock is reported fixed capital, less reported depreciation. Worker composition is measured by the share of workers across education bins. Regional wage distributions are calculated from the 0.5% sample of the 2005 China Population Census. The census contains information on education level by prefecture of residence, occupation, industry code, monthly income and weekly hours of work. We restrict the sample to employees age 15 to 65 who report positive wages and hours of work. The regional wage distribution is recovered from the average annual income of employees by education using census data.[16] Since

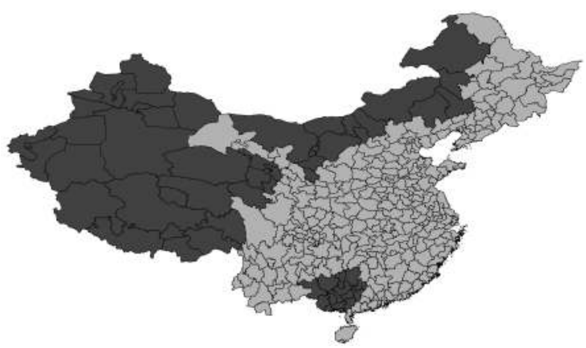
[16]The census data is highly representative of the firm wage data, as discussed in the Appendix.

our firm data is from 2004 and our census data is from 2005, one potential concern is any discrepancy that might be caused by the lag between when these datasets were collected. Fortunately, the assumption that firm skill mix is stable over time is reasonable based on existing studies.[17]

In addition, we use geographic data. One source is GIS data for the year 2005 to locate firms at the county and prefecture level, available from the China Data Center at the University of Michigan. This also provides sea port locations. This is supplemented by inland port data from The World Port Index

Since regions in China are quite heterogeneous, the first consideration is to restrict the data to qualitatively comparable regions. Figure 5.1 illustrates the prefectures of China, which we take as our definition of a region from the perspective of the model above. Prefectures illustrated by a darker shade in the Figure are excluded from the analysis, as they operate under substantially different government policies and objectives. These regions typically have large minority populations or historically distinct conditions, with the majority being declared autonomous regions. Autonomous regions have their own regulations development and educational policies (see the Information Office of the State Council of the People's Republic of China document cited). We restrict attention to the lighter shaded regions of Figure 5.1, preserving 284 prefectures displaying distinct labor market conditions.

Figure 5.1: Chinese Prefectures



- 33 Provinces, excluding:
  - 5 Autonomous
  - 1 Non-Autonomous
- 345 Prefectures, excluding:
  - 53 Autonomous
  - 8 Non-Autonomous

5.2 Regional Variation

Key to our analysis is regional variation in skill distribution and wages. Here we briefly discuss both. Further discussion may be found in Appendix C. Monthly incomes vary sub-

[17] Ilmakunnas and Ilmakunnas (2011) find the standard deviation of plant-level education years is very stable from 1995-2004 in Finland. Parrotta, Pozzoli, and Pytlikova (2011) find that a firm-level education diversity index was roughly constant over a decade in Denmark.

stantially across China as illustrated in Figure 5.2. This is due to both the composition of skills (proxied by education) across regions as well as the rates paid to these skills.

Figure 5.2: Average Monthly Income of Employees (2005)

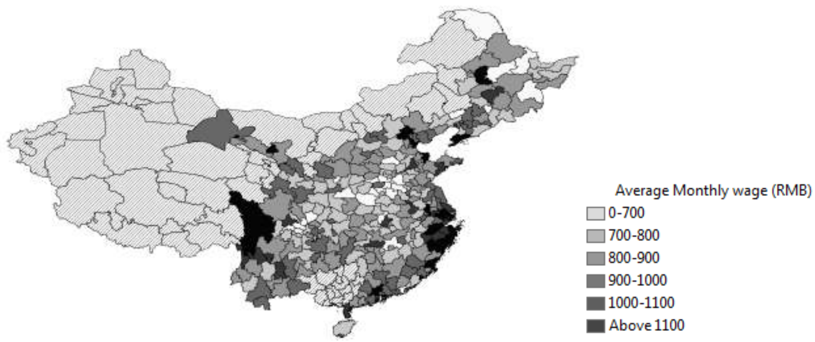
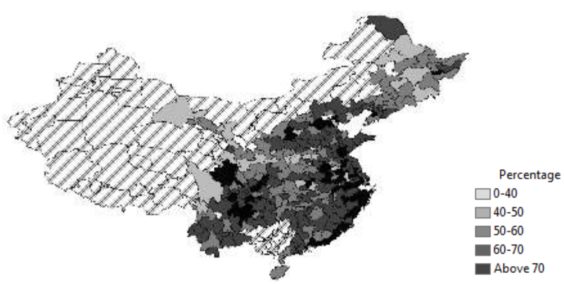


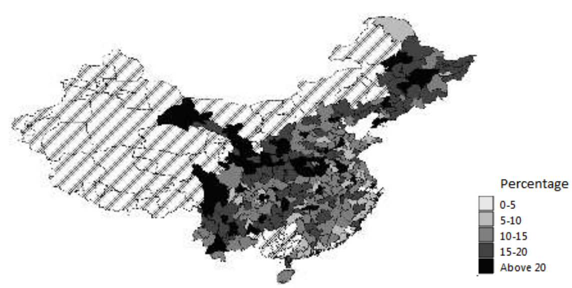
Figure 5.3 contrasts educational distributions of the labor force. Figure 5.3(a) shows those with a Junior High School education (the mandated level in China), while Figure 5.3(b) displays those with a Junior College or higher level of attainment. A more detailed breakdown of the distribution of wages and educational attainment is presented in Appendix C.

Figure 5.3: Low and High Educational Attainment Across China (2005)

(a) % Labor Force with $\leq$ Junior High School



(b) % Labor Force with $\geq$ Junior College



While this study focuses on the differing composition of input markets across China as they exist in 2004-2005, some brief remarks are in order about the origins of these substantial differences.[18] These differences stem from many factors, including the dynamic nature of China's rapidly growing economy, targeted economic policies and geographic agglomeration of industries across China. Faber (2012) finds that expansion of China's National Trunk Highway System displaced economic activity from counties peripheral to the System. Similarly, Baum-Snow, Brandt, Henderson, Turner, and Zhang (2012) show that mass

[18]We consider regional price variation at a fixed point in time. Reallocation certainly occurs and is very important in explaining dynamics (e.g. Borjas (2003)) but are outside the scope of this paper.

transit systems in China have increased the population density in city centers, while radial highways around cities have dispersed population and industrial activity. An overview of important Chinese economic policies is also provided by Fabrice Defever and Alejandro Riano (2012), who quantify their impact on firms.

Of particular interest for labor markets are substantial variation in wages and the attendant migration this induces. The extent to which labor market migration has been stymied by the *hukou* system of internal passports is not well studied, although its impact has likely lessened since 2000.[19] Given that rural to urban migration typifies the pattern of structural transformation currently underway in China, we control for rural and urban effects for each type of worker below. Nonetheless, it remains unclear to what degree the hukou system alters labor flows under the present system. In particular, high income and highly educated workers can more easily move among urban regions as local governments are likely to approve their migration applications (Chan, Liu, and Yang, 1999). It therefore seems likely that the size of labor markets accessible to workers is extremely heterogeneous. Given what little is known about the actual determinants of migration in China, modeling firm decisions when faced with dynamically changing input markets is an interesting avenue for further work.

5.3 Worker Types

Our definition of distinct, imperfectly substitutable worker types is based primarily on formal schooling attained. Census data from 2005 shows that the average years of schooling for workers in China ranges from 8.5 to 11.8 years across provinces, with sparse postgraduate education. The most common level of formal education is at the Junior High School level or below. Reflecting substantial wage differences by gender within that group, we define Type 1 workers as Junior High School or Below: Female and Type 2 workers as Junior High School or Below: Male. Explicit differentiation in the role of gender for low skill labor is especially important in developing countries, where a variety of influences result in imperfect substitutability across gender.[20] Completion of Senior High School defines Type 3 and completion of Junior College or higher education defines Type 4.

Having discussed the data, we now apply the estimation procedure developed above.

[19]The Hukou system and its reform in the late 1990s are well explained in Chan and Buckingham (2008). The persistence of such a stratified system has engendered deep set social attitudes which likely affect economic interactions between Hukou groups, see Afridi, Li, and Ren (2012).

[20]Bernhofen and Brown (2011) distinguish between skilled male labor, unskilled male labour and female labour and find that the factor prices across these three types of labor differ substantially.

6 Estimation Results

This section reports our estimation results, then turns to a discussion of the quantitative labor cost and productivity differences accounted for by local market conditions in China. The section continues by testing the firm location implications of the model, finding broad support that economic activity locates where estimated unit labor costs are lower. Finally, we compare estimation results of our unit cost based method with one approach common in the literature, which assumes that labor types are perfectly substitutable.

6.1 Estimates of Market Conditions and Production Technologies

The full first stage regression results for several manufacturing industries in China are presented in Tables 14 and 15 of Appendix D.2. A representative set of estimates for the General Machinery industry are presented in Table 1. The first box in Table 1, labeled Primary Variables, are consistent with the model. Though values for the coefficients $\left(\theta^T/\beta^T\right)\ln \underline{m}_i/\underline{m}_4$ are not specified by the model, their estimated values do increase in type in Table 1, which is consonant with formal education increasing worker output.

Table 1: First Stage Results: General Machinery

Primary Variables	$\ln(\%\text{ Hired})$
$\ln(w_{R,i})$	-2.687***
$\ln(a_{R,i})$	1.794***
$\underline{m}_1$ ($\leq$Junior HS: Female)	-10.170***
$\underline{m}_2$ ($\leq$Junior HS: Male)	-6.171***
$\underline{m}_3$ (Senior High School)	-3.180***

Regional Controls	
$\underline{m}_1$*% Non-Ag Hukou	-5.957***
$\underline{m}_2$*% Non-Ag Hukou	-3.072***
$\underline{m}_3$*% Non-Ag Hukou	-3.218***
$\underline{m}_4$*% Non-Ag Hukou	-7.026***
Observations: 62,908. R^2 : 0.139	

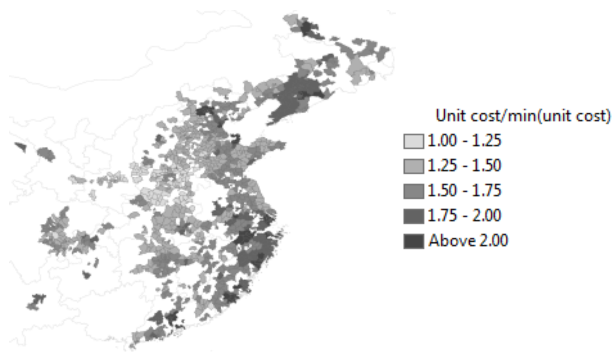
Firm Controls	
$\underline{m}_1 *$ Urban Dummy	-1.384***
$\underline{m}_2 *$ Urban Dummy	-0.980***
$\underline{m}_3 *$ Urban Dummy	0.427***
$\underline{m}_4 *$ Urban Dummy	2.336***
$\underline{m}_1$*% Foreign Equity	-2.448***
$\underline{m}_2$*% Foreign Equity	-1.864***
$\underline{m}_3$*% Foreign Equity	0.311***
$\underline{m}_4$*% Foreign Equity	3.847***
$\underline{m}_1 * \ln(\text{Firm Age})$	0.934***
$\underline{m}_2 * \ln(\text{Firm Age})$	0.403***
$\underline{m}_3 * \ln(\text{Firm Age})$	0.143***
$\underline{m}_4 * \ln(\text{Firm Age})$	0.351***
Includes Regional Fixed Effects	

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

The remaining two boxes include regional controls from the Census and firm level controls from the manufacturing survey. The regional controls are by prefecture, and include the percentage of each type with a non-agricultural Hukou. The firm level controls include the share of foreign equity, the age of the firm, and whether the firm is in an urban area. Inclusion of controls for average worker age, which control for accumulated skill or vintage human capital, do not appreciably alter the results. Other controls which did not appreciably alter the results include State Ownership and the percentage of migrants in a region.

These first stage estimates are interesting in themselves, as the model above allows us to use these estimates to construct the unit cost function for labor by region. We will quantify this shortly, but to continue with the example of the General Purpose Machine industry, the implied dispersion of unit labor costs are depicted in Figure 6.1.

Figure 6.1: Geographic Dispersion of Unit Labor Costs: General Machinery



The model primitives of our two stage estimation procedure across industries are summarized in Tables 2 and 3. Standard errors are calculated using a bootstrap procedure stratified on industry and region, presented in the Appendix. Table 2 displays the estimated model primitives, showing a range of significantly different technologies θ^T and match quality distributions through k. Table 3 shows the second stage estimation results when the regional unit labor costs are calculated using regional data and the first stage estimates.

Table 2: Model Primitive Estimates

Industry	k	θ	β	Industry	k	θ	β
Beverages	2.12	1.24	0.75	Paper	6.25	0.73	2.48
Electrical Equipment	2.60	1.22	0.65	Plastic	3.51	1.08	0.81
Food Manufacturing	1.59	1.28	0.86	Printing	3.93	1.04	0.89
General Machinery	2.50	1.22	0.68	Radio TV PC & Comm	2.21	1.41	0.51
Iron and Steel	3.21	1.00	1.02	Rubber	1.63	1.15	0.93
Leather & Fur	2.15	0.76	1.24	Specific Machinery	1.63	1.43	0.74
Med, Prec Equip, Clocks	2.34	1.43	0.43	Textile	3.73	0.95	1.15
Metal Products	3.20	1.10	0.77	Transport Equipment	1.26	1.38	0.92
Non-ferrous Metal	2.89	1.15	0.72	Wood	1.52	1.62	0.71
Non-metallic Products	2.02	1.25	0.75				

Table 3: Second Stage Estimates

Industry	α_L	α_K	α_M	Industry	α_L	α_K	α_M
Beverages	0.13	0.10	0.70	Paper	0.18	0.14	0.53
Electrical Equipment	0.25	0.14	0.47	Plastic	0.27	0.14	0.41
Food Manufacturing	0.14	0.09	0.70	Printing	0.09	0.22	0.55
General Machinery	0.17	0.12	0.60	Radio TV PC & Comm	0.16	0.21	0.43
Iron and Steel	0.40	0.07	0.48	Rubber	0.06	0.13	0.63
Leather & Fur	0.10	0.13	0.59	Specific Machinery	0.10	0.16	0.55
Med, Prec Equip, Clocks	0.20	0.16	0.43	Textile	0.12	0.11	0.61
Metal Products	0.24	0.14	0.46	Transport Equipment	0.04	0.15	0.65
Non-ferrous Metal	0.40	0.08	0.43	Wood	0.22	0.10	0.56
Non-metallic Products	0.20	0.07	0.61				

While the capital coefficients may seem low, they are not out of line with other estimates which specifically account for material inputs (e.g. Javorcik (2004)). For the specific case of China, there are few studies estimating production coefficients.[21] The most comparable study is Fleisher and Wang (2004) who find microeconomic estimates for α_K in the range of .40 to .50 (which does not differentiate between capital and materials) and these estimates compare favorably with the combined estimates of $\alpha_K + \alpha_M$ in Table 3.

6.2 Implied Productivity Differences Across Firms

Table 4 quantifies the implied differences in unit labor costs and productivity across regions implied by Table 2. The c_R^T column of Table 4 displays the interquartile (75%/25%) unit labor cost ratios by industry, where unit labor costs have been calculated according to the model. The u_R^T column of Table 4 contains the differences in productivity implied by unit labor cost differences, taking into account second stage production parameter estimates. Specifically, if firms 1 and 2 face unit labor costs of c_{RT}^1 and c_{RT}^2 and have the same wage bill W, they will employ labor of $L^1 = W/c_{RT}^1$ and $L^2 = W/c_{RT}^2$. Thus if these firms hire the same capital and material inputs (K, M), then the ratio of their output is

$$Y^1/Y^2 = \left(M^{\alpha_M^T} K^{\alpha_K^T} L_1^{\alpha_L^T}\right) / \left(M^{\alpha_M^T} K^{\alpha_K^T} L_2^{\alpha_L^T}\right) = (L_1/L_2)^{\alpha_L^T} = \left(c_{RT}^2/c_{RT}^1\right)^{\alpha_L^T}.$$

For example, contrast two firms in General Machinery at the 25th and 75th unit labor cost percentile. If both firms have the same wage bill, the labor (L) available to the lower cost

[21] Though not directly comparable, macroeconomic level estimates include Chow (1993) and Ozyurt (2009) who find much higher capital coefficients. These studies do not account for materials.

firm is 1.41 times greater than the higher cost firm. From Table 3 above, the estimated share of wages in production is $\alpha_L^T = 0.17$, so the lower cost firm will produce $1.41^{0.17} = 1.06$ times as much output as the higher cost firm, holding all else constant.

Table 4: Intraindustry Unit Labor Cost and Productivity Ratios

Industry	c_R^T 75/25	u_R^T 75/25	Industry	c_R^T 75/25	u_R^T 75/25
Beverages	1.51	1.06	Paper	1.66	1.07
Electrical Equipment	1.38	1.08	Plastic	1.35	1.09
Food Manufacturing	1.81	1.09	Printing	1.37	1.03
General Machinery	1.41	1.06	Radio TV PC & Comm	1.44	1.06
Iron and Steel	1.34	1.13	Rubber	2.16	1.04
Leather & Fur	1.92	1.04	Specific Machinery	1.99	1.08
Med, Prec Equip, Clocks	1.80	1.13	Textile	1.37	1.04
Metal Products	1.33	1.07	Transport Equipment	4.01	1.04
Non-ferrous Metal	1.45	1.17	Wood	1.47	1.10
Non-metallic Products	1.42	1.08			

Table 4 indicates that the range of total unit costs faced by firms within the same industry are indeed substantial, even after explicitly taking into account the technology θ^T and the ability to substitute across several types of workers. However, the second stage estimates indicate these differences are attenuated by substitution into capital and materials. Thus, while differences in regional markets indicate an interquartile range of 30-80% in unit cost differences, substitution into other factors reduces this range to between 3-17%. These rather substantial differences reiterate an important issue raised by Kugler and Verhoogen (2011): since TFP is often the 'primary measure of [...] performance', accounting for local factor markets might substantially alter estimates of policy effects.

Since firms locate freely, the model predicts that these substantial cost differences drive economic activity towards more advantageous locations, which we now examine.

6.3 Firm Location

Per capita volumes of economic activity across regions are determined by Equation (3.7), which states that relatively lower industry labor costs should attract relatively more firms to a region. Table 7 summarizes estimates of this relationship, controlling for regional distance to the nearest port (weighted by the share of value added in a region). Whenever the relationship between value added and labor costs is statistically significant, the relationship is negative, in line with the model.[22]

Table 5: Determinants of Regional (Log) Value Added per Capita

Industry	$\ln\left(c_R^T\right)$	Std Err	100 km to Port	Std Err	Const	Std Err	Obs	R^2
Beverages	-0.696^b	(.274)	-0.122	(.200)	18.96^a	(3.36)	155	.03
Electrical Equipment	-0.057	(.403)	-1.567^a	(.259)	11.98^b	(4.80)	166	.22
Food Manufacturing	-0.553^b	(.229)	-0.397^b	(.179)	15.49^a	(2.15)	171	.04
General Machinery	-0.705^c	(.400)	-1.314^a	(.340)	19.68^a	(4.86)	195	.11
Iron and Steel	-1.245^b	(.565)	-0.576^a	(.194)	16.30^a	(2.22)	160	.06
Leather & Fur	-1.255^a	(.249)	-1.028^b	(.421)	25.81^a	(3.05)	89	.27
Med, Prec Equip & Clocks	-0.267	(.300)	-1.135^b	(.432)	13.13^a	(3.39)	68	.07
Metal Products	-0.236	(.463)	-1.239^a	(.260)	13.24^a	(4.86)	157	.14
Non-ferrous Metal	-1.977^a	(.544)	-0.468^c	(.275)	27.29^a	(4.57)	139	.10
Non-metallic Products	-0.827^a	(.290)	-0.910^a	(.155)	20.89^a	(3.38)	259	.11
Paper	-0.911^a	(.197)	-0.320	(.246)	20.04^a	(2.08)	159	.12
Plastic	-0.556	(.352)	-1.406^a	(.221)	16.86^a	(3.99)	159	.22
Printing	0.103	(.655)	-0.123	(.257)	8.54	(7.12)	98	.01
Radio TV PC & Comm	-0.212	(.366)	-0.741^b	(.333)	13.92^a	(4.60)	90	.04
Rubber	-0.424^c	(.219)	-0.470	(.398)	14.06^a	(2.07)	79	.06
Specific Machinery	-0.316^c	(.184)	-0.680^a	(.194)	14.74^a	(2.28)	167	.07
Textile	-0.934^a	(.273)	-1.168^a	(.153)	19.70^a	(2.44)	186	.18
Transport Equipment	-0.105	(.099)	-1.119^a	(.253)	12.69^a	(1.30)	168	.10
Wood	-2.234^a	(.338)	-1.038^a	(.267)	47.02^a	(5.63)	133	.20

Note: a, b and c denote 1, 5 and 10% significance level respectively.

In contrast to the present setting, most firm models used in production function estimation assume perfect labor substitutability. One implication of perfect substitutability is that, conditional on wages, the local composition of the workforce is irrelevant for hiring patterns. We have just seen that our approach, which is more sensitive to local factor market characteristics, helps explain firm location. We now compare out approach with others.

6.4 Comparison with Conventional Labor Measures

The estimates above reflect a procedure using regional variation to recover the unit cost of labor. Often, such information is not incorporated into production estimation. Instead, the number of employees or total wage bill are used to capture the effective labor available to a firm. The estimation results using these labor measures are contrasted with our method

[22] These results are robust if distance is unweighted, and to the inclusion of Economic Zone status.

in Table 6. The production coefficients using the total wage bill or total employment are very similar, reflecting the high correlation of these variables. However, both measures mask regional differences in factor markets. Once local substitution patterns are taken into account explicitly, substantial differences emerge.[23]

Table 6: Second Stage Estimates vs Homogeneous Labor Estimates

	Unit Labor Cost			Total Wage Bill			Total Employment		
Industry	α_L	α_K	α_M	α_L	α_K	α_M	α_L	α_K	α_M
Beverages	0.13	0.10	0.70	0.23	0.06	0.71	0.22	0.07	0.73
Electrical Equipment	0.25	0.14	0.47	0.34	0.12	0.47	0.32	0.12	0.51
Food Manufacturing	0.14	0.09	0.70	0.16	0.06	0.73	0.17	0.06	0.75
General Machinery	0.17	0.12	0.60	0.25	0.09	0.61	0.23	0.09	0.64
Iron and Steel	0.40	0.07	0.48	0.25	0.07	0.68	0.29	0.05	0.70
Leather & Fur	0.10	0.13	0.59	0.27	0.09	0.55	0.30	0.09	0.56
Med, Prec Equip, Clocks	0.20	0.16	0.43	0.44	0.08	0.38	0.36	0.10	0.44
Metal Products	0.24	0.14	0.46	0.30	0.12	0.48	0.30	0.12	0.51
Non-ferrous Metal	0.40	0.08	0.43	0.17	0.10	0.65	0.22	0.08	0.65
Non-metallic Products	0.20	0.07	0.61	0.20	0.06	0.67	0.18	0.06	0.70
Paper	0.18	0.14	0.53	0.28	0.11	0.52	0.31	0.10	0.54
Plastic	0.27	0.14	0.41	0.31	0.13	0.43	0.32	0.13	0.45
Printing	0.09	0.22	0.55	0.40	0.14	0.44	0.34	0.17	0.49
Radio TV PC & Comm	0.16	0.21	0.43	0.48	0.14	0.35	0.40	0.16	0.41
Rubber	0.06	0.13	0.63	0.31	0.07	0.55	0.32	0.06	0.56
Specific Machinery	0.10	0.16	0.55	0.31	0.10	0.48	0.26	0.11	0.52
Textile	0.12	0.11	0.61	0.29	0.07	0.56	0.29	0.06	0.58
Transport Equipment	0.04	0.15	0.65	0.31	0.09	0.53	0.27	0.09	0.57
Wood	0.22	0.10	0.56	0.23	0.08	0.62	0.26	0.07	0.63
Average	0.18	0.13	0.55	0.29	0.09	0.54	0.28	0.09	0.58

Pushing this comparison further, Table 7 predicts the three year survival rate of firms by residual firm productivity. The first column shows the results under our unit cost method. The second and third columns show the results when labor is measured as perfectly substitutable (either by employment or wages). Note that in all cases, regional and industry effects are controlled for. The Table illustrates that productivity estimates which account for regional factor markets are almost twice as important in predicting firm survival as the other measures. Section D.5 of the Appendix shows that similar results hold when examining sales growth and propensity to export: productivity under the unit cost approach is more

[23]The residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity, are compared across methods in the Appendix.

important in predicting firm performance, suggesting the other measures conflate the role of advantageous factor markets with productivity.

Table 7: Explaining Survival with Productivity

	Survival Rate (2005-7)		
Productivity under Unit Cost method	0.019***		
	(0.003)		
Productivity under L =Employment		0.010***	
		(0.002)	
Productivity under L =Wage Bill			0.010***
			(0.002)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.023	0.022	0.022

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

7 Conclusion

This paper examines the importance of local supply characteristics in determining firm input usage and productivity. To do so, a theory and empirical method are developed to identify firm input demand across industries and heterogeneous labor markets. The model derives labor demand as driven by the local distribution of wages and available skills. Firm behavior in general equilibrium is derived, and determines firm location as a function of regional costs. This results in estimating equations which can be easily implemented in two steps. The first step exploits differences in firm hiring patterns across distinct regional factor markets to recover firm labor demand by type. The second step uses the estimates of the first stage to introduce local labor costs into production function estimation. Both steps characterize the impact of local market conditions on firm behavior through recovery of model primitives. This is of particular interest when explaining the relative productivity or location of firms, especially in settings where local characteristics are known to be highly dissimilar.

Our empirical strategy combines information from the Chinese manufacturing, population census, and geographic data from the mid-2000s. The estimates provide a quantitative linkage from local market conditions to productivity. The results suggest that team technologies combined with favorable factor market conditions explain substantial differences in firm productivity. Other methods which do not model worker substitution or factor markets yield relatively skewed productivity estimates in China. This supports the thesis that modeling a firm's local environment may yield substantial insights into production patterns. Our results indicate differences in local markets are quantitatively important.

The importance of local factor markets for understanding firm behavior suggests new dimensions for policy analysis. For instance, regions with labor markets which generate lower unit labor costs tend to attract higher levels of firm activity within an industry. As unit labor costs depend not only on the level of wages, but rather the distribution of wages and worker types that represent substitution options, this yields a more varied view of how educational policy or flows of different worker types could impact firms.

This paper also colors the interpretation of heterogeneous productivity at the firm level, since a component of differences across firms is due to the influence of local supply conditions. Productivity estimates which result from our model are more important in predicting firm performance than models based on perfectly substitutable worker types. This suggests that if firm productivity is a measure of 'competitiveness' leading to dynamic advantages such as innovation or exporting, then regional factor markets should be controlled for. Taken as a whole, our results show that policy changes which influence the composition of regional labor markets, such as the construction of Special Economic Zones or liberalization of the Hukou system, will have sizable effects on firm behavior, productivity and location.

Finally, nothing precludes the application of this paper's approach beyond China, and it is suitable for analyzing regions which exhibit a high degree of labor market heterogeneity. As the model affords the interpretation of trade between countries which have high barriers to immigration but low barriers to capital and input flows, it might also be suitable for analyzing firm behavior across national borders. Further work might leverage or extend the approach of combining firm, census and geographic data to better understand the role of local factor markets in hiring, input usage and firm dynamics.

References

ABOWD, J. M., J. HALTIWANGER, R. JARMIN, J. LANE, P. LENGERMANN, K. MCCUE, K. MCKINNEY, AND K. SANDUSKY (2005): "The Relation among Human Capital, Productivity, and Market Value: Building Up from Micro Evidence," in *Measuring Capital in the New Economy*, NBER Chapters, pp. 153–204. National Bureau of Economic Research.

ABOWD, J. M., F. KRAMARZ, AND D. N. MARGOLIS (1999): "High Wage Workers and High Wage Firms," *Econometrica*, 67(2), pp. 251–333.

ABRAMOVITZ, M. (1956): "Resource and Output Trends in the United States Since 1870," *The American Economic Review*, pp. 5–23.

AFRIDI, F., S. LI, AND Y. REN (2012): “Social Identity and Inequality: The Impact of China’s Hukou System,” *Working Paper*.

ATALAY, E., A. HORTACSU, AND C. SYVERSON (2012): “Why Do Firms Own Production Chains?,” NBER Working Papers 18020, National Bureau of Economic Research, Inc.

BANDIERA, O., I. BARANKAY, AND I. RASUL (2009): “Social Connections and Incentives in the Workplace: Evidence from Personnel Data,” *Econometrica*, 77(4), pp. 1047–1094.

BAS, M., AND V. STRAUSS-KAHN (2012): “Trade Liberalization and Export Prices: The case of China,” *Working Paper*.

BAUM-SNOW, N., L. BRANDT, J. V. HENDERSON, M. A. TURNER, AND Q. ZHANG (2012): “Roads, Railroads and Decentralization of Chinese Cities,” Working paper.

BERNARD, A., S. REDDING, AND P. SCHOTT (2007): “Comparative advantage and heterogeneous firms,” *Review of Economic Studies*, 74(1), 31–66.

BERNHOFEN, D. M., AND J. C. BROWN (2011): “Testing the General Validity of the Heckscher-Ohlin Theorem: The Natural Experiment of Japan,” CESifo Working Paper Series 3586, CESifo Group Munich.

BLOOM, N., AND J. V. REENEN (2007): “Measuring and Explaining Management Practices across Firms and Countries,” *The Quarterly Journal of Economics*, 122(4), pp. 1351–1408.

BLOOM, N., M. SCHANKERMAN, AND J. VAN REENEN (2007): “Identifying Technology Spillovers and Product Market Rivalry,” *National Bureau of Economic Research Working Paper 13060*.

BOMBARDINI, M., G. GALLIPOLI, AND G. PUPATO (2011): “Skill Dispersion and Trade Flows,” *Working Paper Series*.

BORJAS, G. (2009): “The Analytics of the Wage Effect of Immigration,” *Working Paper*.

BORJAS, G. J. (2003): “The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market,” *The Quarterly Journal of Economics*, 118(4), 1335–1374.

BOWLES, S. (1970): “Aggregation of Labor Inputs in the Economics of Growth and Planning: Experiments with a Two-Level CES Function,” *The Journal of Political Economy*, 78(1), 68–81.

BRANDT, L., J. VAN BIESEBROECK, AND Y. ZHANG (2009): “Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing,” Discussion paper, Katholieke Universiteit Leuven.

CHAN, K. W., AND W. BUCKINGHAM (2008): "Is China Abolishing the Hukou System?," *The China Quarterly*, 195, 582–606.

CHAN, K. W., T. LIU, AND Y. YANG (1999): "Hukou and Non-hukou Migrations in China: Comparisons and Contrasts," *International Journal of Population Geography*, 5, 425–448.

CHOW, G. C. (1993): "Capital Formation and Economic Growth in China," *The Quarterly Journal of Economics*, 108, 809–842.

DIVISION OF POLICY & PRACTICE SECTION UNICEF (2008): "Education statistics: China," *Childinfo*, Statistics by country.

FABER, B. (2012): "Trade Integration, Market Size, And Industrialization: Evidence From China's National Trunk Highway System," *Working Paper*.

FABRICE DEFEVER, AND ALEJANDRO RIANO (2012): "Pure-Exporter Subsidies: The Non-Reform of China's Trade Policy," *Working Paper*.

FLEISHER, B. M., AND X. WANG (2004): "Skill differentials, return to schooling, and market segmentation in a transition economy: the case of Mainland China," *Journal of Development Economics*, 73(1), 315–328.

FOX, J. T., AND V. SMEETS (2011): "Does Input Quality Drive Measured Differences in Firm Productivity?," NBER Working Papers 16853, National Bureau of Economic Research.

GARICANO, L., AND P. HEATON (2010): "Information Technology, Organization, and Productivity in the Public Sector: Evidence from Police Departments," *Journal of Labor Economics*, 28(1), 167–201.

GROSSMAN, G. M., AND G. MAGGI (2000): "Diversity and Trade," *The American Economic Review*, 90(5), 1255–1275.

HELPMAN, E., O. ITSKHOKI, AND S. REDDING (2010): "Inequality and Unemployment in a Global Economy," *Econometrica*, 78(4), 1239–1283.

HIRSCHMAN, A. (1958): *The Strategy of Economic Development.* Yale University Press, New Haven.

HORTAÇSU, A., AND C. SYVERSON (2007): "Cementing Relationships: Vertical Integration, Foreclosure, Productivity, and Prices," *Journal of Political Economy*, 115(2), 250–301.

HSIEH, C. T., AND P. J. KLENOW (2009): "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124(4), 1403–1448.

ILMAKUNNAS, P., AND S. ILMAKUNNAS (2011): "Diversity at the Workplace: Whom Does it Benefit?," *De Economist*, 159(2), 223–255.

INFORMATION OFFICE OF THE STATE COUNCIL OF THE PEOPLE'S REPUBLIC OF CHINA (2005): "Regional Autonomy for Ethnic Minorities in China," *Chinese government's official web portal*.

IRANZO, S., F. SCHIVARDI, AND E. TOSETTI (2008): "Skill Dispersion and Firm Productivity: An Analysis with Employer-Employee Matched Data," *Journal of Labor Economics*, 26(2), 247–285.

JAVORCIK, B. S. (2004): "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages," *American Economic Review*, 94(3), 605–627.

KARADI, P., AND M. KOREN (2012): "Cattle, Steaks and Restaurants: Development Accounting when Space Matters," *Working Paper*.

KENNAN, J., AND J. R. WALKER (2011): "The effect of expected income on individual migration decisions," *Econometrica*, 79(1), 211–251.

KUGLER, M., AND E. VERHOOGEN (2011): "Prices, Plant Size, and Product Quality," *The Review of Economic Studies*, 79(1), 307–339.

LAZEAR, E. P. (2000): "Performance Pay and Productivity," *The American Economic Review*, 90(5), pp. 1346–1361.

LEWIS, W. (1954): "Economic development with unlimited supplies of labour," *The Manchester School*, 22(2), 139–191.

MA, Y., H. TANG, AND Y. ZHANG (2011): "Factor Intensity, Product Switching, and Productivity: Evidence from Chinese Exporters," Development Working Papers 324, Centro Studi Luca dÁgliano, University of Milano.

MANOVA, K., AND Z. ZHANG (2012): "Export Prices Across Firms and Destinations," *The Quarterly Journal of Economics*, 127(1), 379–436.

MARTINS, P. S. (2008): "Dispersion in wage premiums and firm performance," *Economics Letters*, 101(1), 63–65.

MELITZ, M. J. (2003): "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," *Econometrica*, 71(6), 1695–1725.

MORETTI, E. (2004): "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions," *American Economic Review*, 94(3), 656–690.

——— (2011): "Chapter 14 - Local Labor Markets," vol. 4, Part B of *Handbook of Labor Economics*, pp. 1237 – 1313. Elsevier.

MORROW, J. (2010): "Is Skill Disperison a Source of Productivity and Exports in Developing Countries?," *Working Paper*.

OTTAVIANO, G., AND G. PERI (2010): "Rethinking the Effect of Immigration on Wages," *Working Paper*.

OVERMAN, H. G., AND D. PUGA (2010): "Labor pooling as a source of agglomeration: An empirical investigation," in *Agglomeration Economics*, ed. by Edward L. Glaeser. University of Chicago Press.

OZYURT, S. (2009): "Total Factor Productivity Growth in Chinese Industry: 1952-2005," *Oxford Development Studies*, 37(1), 1–17.

PARROTTA, P., D. POZZOLI, AND M. PYTLIKOVA (2011): "Does Labor Diversity affect Firm Productivity?," Norface Discussion Paper Series 2011022, Norface Research Programme on Migration, Department of Economics, University College London.

SYVERSON, C. (2004): "Market Structure and Productivity: A Concrete Example," *Journal of Political Economy*, 112(6), 1181–1222.

——— (2011): "What Determines Productivity?," *Journal of Economic Literature*, 49(2), 326–365.

TOPALOVA, P. (2010): "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India," *American Economic Journal: Applied Economics*, 2(4), 1–41.

A Further Model Discussion and Proofs

A.1 Relative Prices and Limited Factor Price Equalization

The formula for unit labor costs shows that regions with different skill distributions, say region R and R', typically cannot have both $c_R^T = c_{R'}^T$ and $w_R = w_{R'}$. However, factor price equalization for labor holds in a limited fashion in two ways. First, Equation (3.4) a limited form of factor price equalization holds within each industry: the industry wage bill *per capita* is equalized, formally

$$c_R^T L_R^T / \mathbb{P}_R = c_{R'}^T L_{R'}^T / \mathbb{P}_{R'} \text{ for all region pairs } \left(R, R'\right).$$

Second, since $\sum_i \widetilde{w}_{R,i}^T = 1$, (3.6) implies

$$\text{Average Wages}: \quad \sum_i a_{R,i} w_{R,i} = \sum_t \alpha_L^t \sigma^t I_{\text{Agg}},$$

i.e. that average wages are constant across regions, despite differences in unit labor costs.

A.2 Existence of Regional Wages to Clear Input Markets

What is required is to exhibit a wage vector $\{w_{R,i}\}$ that ensures Equation (3.6) holds. Since all prices are nominal, WLOG we normalize $I_{\text{Agg}} = 1$ in the following.

Lemma. *There is a wage function that uniquely solves (3.6) given unit labor costs.*

Proof. Formally, we need to exhibit $\mathbb{W}$ such that

$$a_{R,i} = \mathbb{W}_{R,i} \left(\left\{ c_{R'}^{T'} \right\} \right)^{-1} \sum_t \alpha_L^t \sigma^t \left(c_R^t \right)^{k/\beta^t - 1} \left(\frac{\mathbb{W}_{R,i} \left(\left\{ c_{R'}^{T'} \right\} \right)^{1-k} a_{R,i} \left(\underline{m}_i^t \right)^k}{f \left(k-1 \right)} \right)^{\theta^t / \beta^t} \quad \forall R, i.$$

Fix $\left\{ c_{R'}^{T'} \right\}$ and define $h_{R,i}(x) \equiv \sum_t \alpha_L^t \sigma^t \left(c_R^t \right)^{k/\beta^t - 1} \left(x^{1-k} a_{R,i} \left(\underline{m}_i^t \right)^k / f(k-1) \right)^{\theta^t/\beta^t}$, $g_{R,i}(x) \equiv a_{R,i} x$. For the result we require a unique x s.t. $g_{R,i}(x) = h_{R,i}(x)$. $g_{R,i}$ is strictly increasing and ranges from 0 to ∞, while $h_{R,i}(x)$ is strictly decreasing, and ranges from ∞ to 0, so x exists and is unique. $\square$

Lemma. *The function $\left\{ c_R^T \circ \mathbb{W} \left(\left\{ c_R^T \right\} \right) \right\}$, where c_R^T is the unit cost function of Equation (2.10), has a fixed point $\left\{ \widehat{c}_R^T \right\}$ and so $\mathbb{W} \left(\left\{ \widehat{c}_R^T \right\} \right)$ is a solution to Equation (3.6).*

Proof. We first show that any equilibrium wage vector must lie in a compact set $\times_{R,i}\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]$ which contains strictly positive values. From (3.6), $\widetilde{w}^T_{R,i}\in[0,1]$ so $w_{R,i}\leq\overline{w}_{R,i}\equiv\sum_t\alpha^t_L\sigma^t/a_{R,i}$. Now let

$$\underline{b}_R\equiv\min_i\sum_t\alpha^t_L\sigma^t\left(a_{R,i}\left(\underline{m}^t_i\right)^k\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}^t_i\right)^k\right]^{\theta^t/\beta^t}a_{R,i},$$

and we will show that a lower bound for equilibrium wages is $\underline{w}_R\equiv\left[\begin{array}{ccc}\underline{b}_R, & \ldots, & \underline{b}_R\end{array}\right]$ for each R. Consider that for $\mathbb{W}$ evaluated at $\left\{c^T_R\left(\underline{w}_R\right)\right\}$,

$$\mathbb{W}_{R,i}=\sum_t\alpha^t_L\sigma^t\left(a_{R,i}\left(\underline{m}^t_i\right)^k\left(\mathbb{W}_{R,i}/\underline{w}_R\right)^{1-k}\right)^{\theta^t/\beta^t}/\sum_i\left[a_{R,i}\left(\underline{m}^t_i\right)^k\right]^{\theta^t/\beta^t}a_{R,i}. \qquad \text{(A.1)}$$

Evaluating Equation (A.1), if $\mathbb{W}_{R,i}\leq\underline{w}_R$ then $\mathbb{W}_{R,i}\geq\underline{w}_R$, and otherwise, $\mathbb{W}_{R,i}\geq\underline{w}_R$ so $\{\underline{w}_R\}$ is a lower bound for $\mathbb{W}\left(\left\{c^T_R\left(\underline{w}_R\right)\right\}\right)$. Since necessarily $\mathbb{W}\left(\left\{c^T_R\left(\hat{w}_R\right)\right\}\right)=\{\hat{w}_R\}$, $\mathbb{W}$ is increasing in $\left\{c^T_R\right\}$, and $c^T_R\left(w_R\right)$ is increasing in w_R, we have $\{\hat{w}_R\}=\mathbb{W}\left(\left\{c^T_R\left(\hat{w}_R\right)\right\}\right)\geq\mathbb{W}\left(\left\{c^T_R\left(\underline{w}_R\right)\right\}\right)\geq\{\underline{w}_R\}$. In conclusion, all equilibrium wages must lie in $\times_{R,i}\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]$.

Now define a strictly positive, compact domain for $\left\{c^T_R\right\}$, $\times_R\left[\underline{c}^T_R,\overline{c}^T_R\right]$, by

$$\underline{c}^T_R\equiv\inf_{\times_i\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]}c^T_R\left(w_R\right)=c^T_R\left(\underline{w}_R\right),\qquad\overline{c}^T_R\equiv\sup_{\times_i\left[\underline{w}_{R,i},\overline{w}_{R,i}\right]}c^T_R\left(w_R\right)=c^T_R\left(\overline{w}_R\right).$$

Now consider the mapping $\mathbb{C}\left(\left\{c^T_R\right\}\right)\equiv\left\{c^T_R\circ\mathbb{W}\left(\left\{c^T_R\right\}\right)\right\}$ on $\times_R\left[\underline{c}^T_R,\overline{c}^T_R\right]$, which is continuous on this domain. By above, $\mathbb{W}_{R,i}\left(\left\{c^T_R\right\}\right)\leq\overline{w}_{R,i}$ for each R,i so $\mathbb{C}\left(\left\{c^T_R\right\}\right)\leq\left\{\overline{c}^T_R\right\}$. Also by above, $\mathbb{C}\left(\left\{c^T_R\right\}\right)\geq\left\{c^T_R\circ\mathbb{W}\left(\left\{c^T_R\left(\underline{w}_R\right)\right\}\right)\right\}\geq\left\{c^T_R\left(\{\underline{w}_R\}\right)\right\}=\left\{\underline{c}^T_R\right\}$. Thus $\mathbb{C}$ maps $\times_R\left[\underline{c}^T_R,\overline{c}^T_R\right]$ into itself and by Brouwer's fixed point theorem, there exists a fixed point $\left\{\widehat{c}^T_R\right\}$, which implies $\mathbb{W}\left(\left\{\widehat{c}^T_R\right\}\right)$ is an equilibrium wage vector. □

B Model Simulation and Estimator Viability

A model simulation was constructed using parameters given in Table 8. In the simulation, firms maximize profits conditional on local market conditions, and applying the procedure above produces Tables 9a and 9b. The estimation results are given in the Estimate column while the model analytical values are reported in the Predicted column. The results are quite satisfactory, insofar as the estimates are not only consistent but also close to the predicted values. Figure B.1 further confirms this by plotting the simulated and predicted differences in the share of workers hired. For ease of comparison across panels, Figure B.1 plots regional frequencies along the horizontal axis and (linearly) normalized wages for each worker type.

As suggested by the Figure, the adjusted R^2 in both cases are quite high: .99 for the first stage and .97 for the second stage.

Table 8: Simulation details

Variable	**Description**	**Value**
θ^T	Technological parameter.	2
k	Pareto shape parameter.	1.5
$\{\underline{m}_i\}$	Human capital shifters.	$\{4,8,12,16,20\}$
$\{w_{R,i}\}$	Regional wages by type.	$\sim$LogNormal $\mu=(12,24,36,48,60)$, $\sigma=1/3$.
$\{a_{R,i}\}$	Regional type frequencies.	$\sim$LogNormal $\mu=(.4,.3,.15,.1,.05)$, $\sigma=1/3$, scaled so that frequencies sum to one.
K, M	Firm capital and materials.	$\sim$LogNormal $\mu=1$, $\sigma=1$.
L	Level of L employed by firm.	Profit maximizing given K, M and region.
$\alpha_M,\alpha_K,\alpha_L$	Production Parameters.	$\alpha_M=1/6$, $\alpha_K=1/3$, $\alpha_L=1/2$.
Control	Misc variable for output.	$\sim$LogNormal $\mu=0$, $\sigma=1$.
Coeff	Exponent on Control.	Control Coeff$=\pi$.
$\{\omega_j\}$	Firm idiosyncratic wage costs.	$\sim$LogNormal $\mu=0$, $\sigma=.1$.

Sample: 200 regions with 20 firms per region, with errors $\sim$LogNormal($\mu=0$, $\sigma=1/2$).

Table 9: Simulation Results

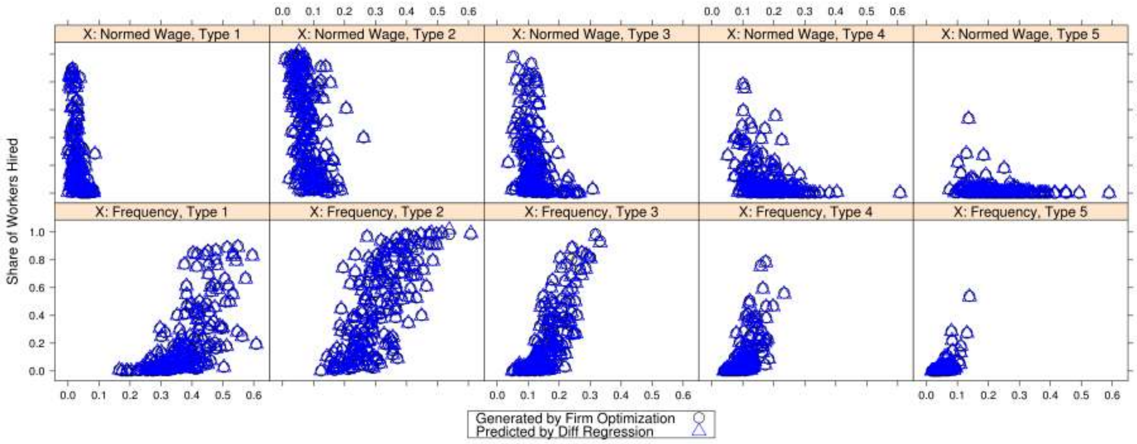
(a) Simulation First Stage Estimates: Technology and Human Capital

Variable	**Parameter**	**Estimate**	**Std Err**	**Predicted**
$\{\ln a_{R,i}\}$	(θ^T/β^T)	3.912	.0019	4
$\{\ln w_{R,i}\}$	$(-k/\beta^T)$	-2.922	.0021	-3
Dummy (Type = 1)	$(\theta^T/\beta^T)\,k\,(\ln \underline{m}_1/\underline{m}_5)$	-9.376	.0057	-9.657
Dummy (Type = 2)	$(\theta^T/\beta^T)\,k\,(\ln \underline{m}_2/\underline{m}_5)$	-5.295	.0045	-5.498
Dummy (Type = 3)	$(\theta^T/\beta^T)\,k\,(\ln \underline{m}_3/\underline{m}_5)$	-2.950	.0031	-3.065
Dummy (Type = 4)	$(\theta^T/\beta^T)\,k\,(\ln \underline{m}_4/\underline{m}_5)$	-1.274	.0024	-1.339

(b) Simulation Second State Estimates: Production Parameters

Variable	**Parameter**	**Estimate**	**Std Err**	**Predicted**
$\ln M$	$\alpha_M/(1-\alpha_L)$	.3298	.0079	.3333
$\ln K$	$\alpha_K/(1-\alpha_L)$	.6680	.0080	.6667
$\ln c_{RT}$	$-\alpha_L/(1-\alpha_L)$	-.9303	.0748	-1
Control	Control Coeff	3.148	.0079	3.141

Figure B.1: Simulation Fit



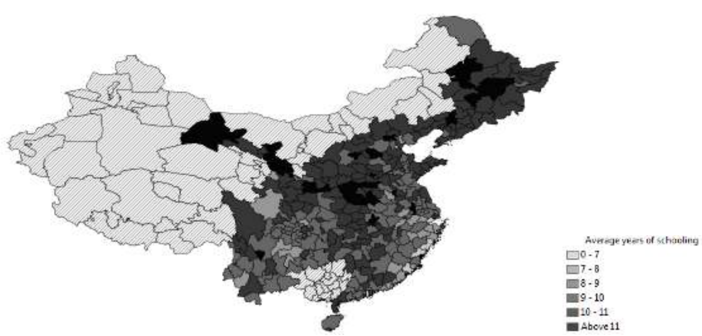
C Further Details on Regional Variation In China

C.1 Educational Summary Statistics

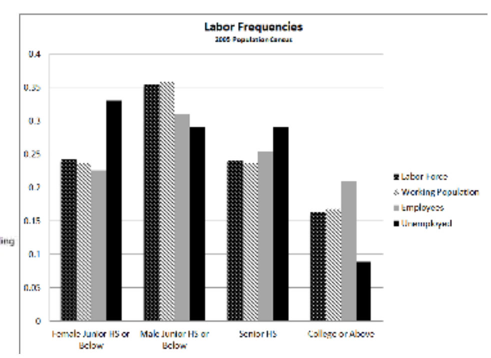
Figures C.1a and C.1b reveal more details about regional variation across China. Figure C.1a illustrates the average years of schooling for the Chinese labor force.

Figure C.1: Chinese Educational Attainment (2005)

(a) Labor Force Schooling (2005)



(b) Distribution of Attainment (2005)



UNICEF suggests that the typical Chinese primary school entrance age is 7. Compulsory education lasts nine years (primary and secondary school) and ends around age sixteen. Figure C.1b illustrates the distribution of education by classification of (potential) workers. In the Figure, the Labor Force includes both workers and the unemployed. Workers are those of age 15 to 65 who work outside the agricultural sector. Employees is the subset of workers who are not employers, self-employed, or in a family business. Figure C.1b illustrates that the frequency of each type of worker under each of these definitions of labor. The measures are quite similar, with the exception that unemployment is more prevalent among the less skilled.

Table 10: Educational and Wage Distribution by Province (2005)

Province	Fraction of Labor Force by Education				Avg Monthly Wage by Education			
	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above	≤Junior HS (Female)	≤Junior HS (Male)	Senior HS	College or Above
Anhui	0.296	0.485	0.155	0.063	581	862	866	1210
Beijing	0.140	0.284	0.299	0.277	796	1059	1314	2866
Chongqing	0.272	0.408	0.227	0.093	582	820	872	1379
Fujian	0.348	0.453	0.146	0.052	695	942	1103	1855
Gansu	0.216	0.399	0.271	0.114	507	738	869	1135
Guangdong	0.327	0.362	0.231	0.080	748	967	1281	2719
Guizhou	0.292	0.478	0.162	0.069	572	758	925	1189
Hainan	0.328	0.334	0.259	0.080	532	694	894	1527
Hebei	0.230	0.515	0.190	0.066	515	793	832	1233
Heilongjiang	0.217	0.393	0.285	0.104	515	740	797	1096
Henan	0.229	0.428	0.234	0.109	487	675	714	1079
Hubei	0.271	0.384	0.264	0.081	541	757	809	1262
Hunan	0.263	0.444	0.229	0.063	634	828	889	1267
Jiangsu	0.314	0.400	0.210	0.076	758	994	1086	1773
Jiangxi	0.291	0.456	0.196	0.056	525	783	794	1240
Jilin	0.204	0.382	0.307	0.107	522	745	809	1163
Liaoning	0.250	0.410	0.219	0.120	576	822	848	1366
Shaanxi	0.203	0.406	0.277	0.114	497	731	805	1149
Shandong	0.288	0.441	0.203	0.068	602	823	863	1398
Shanghai	0.221	0.321	0.272	0.186	891	1155	1450	3085
Shanxi	0.169	0.520	0.221	0.089	502	872	857	1113
Sichuan	0.277	0.480	0.162	0.081	541	737	829	1477
Tianjin	0.258	0.321	0.285	0.136	995	1019	1074	1617
Yunnan	0.275	0.495	0.160	0.070	504	697	896	1542
Zhejiang	0.357	0.469	0.129	0.045	817	1097	1299	2333

C.2 Provincial Summary Statistics

Table 11: Descriptive Statistics by Province (2005)

	Manufacturing		Population Census			
	Firm	Avg	# of	# Region-	Monthly	Avg Yrs
Province	Count	Workers	Regions	Industries	Wage	School
Anhui	2,296	208	17	822	832	8.925
Beijing	3,676	145	2	128	1665	11.542
Chongqing	1,574	287	3	184	862	9.606
Fujian	7,534	212	9	504	945	8.170
Gansu	461	274	14	658	805	9.728
Guangdong	21,575	275	21	1269	1137	9.607
Guizhou	812	246	9	464	805	8.565
Hainan	126	149	3	151	830	9.772
Hebei	5,104	231	11	623	781	9.527
Heilongjiang	921	256	13	622	774	10.197
Henan	5,849	228	17	798	720	10.053
Hubei	2,685	247	14	742	789	9.731
Hunan	3,500	195	14	751	843	9.588
Jiangsu	22,197	170	13	756	1013	9.431
Jiangxi	1,501	245	11	556	766	9.208
Jilin	927	274	9	477	796	10.340
Liaoning	5,141	170	14	770	865	10.152
Shaanxi	1,207	368	10	548	787	10.068
Shandong	12,958	216	17	947	825	9.596
Shanghai	9,857	147	2	119	1577	10.569
Shanxi	1,118	386	11	619	847	9.895
Sichuan	3,209	238	21	887	800	9.149
Tianjin	2,671	195	2	128	1119	10.243
Yunnan	733	240	16	695	794	8.675
Zhejiang	27,639	144	11	629	1098	8.201

C.3 Industrial Summary Statistics

Table 12 presents the distribution of firms by industry and other descriptive statistics.

Table 12: Manufacturing Survey Descriptive Statistics (2005)

				Share of				
Industry	# of firms	# of Regions	Avg # of workers	Female	White Collar	Export	State Equity	Foreign Equity
Beverages	2,225	155	219.20	0.281	0.114	0.150	0.107	0.121
Electrical Equipment	12,241	166	201.58	0.289	0.106	0.351	0.030	0.195
Food Manufacturing	3,807	171	193.98	0.321	0.091	0.266	0.060	0.202
General Machinery	15,727	195	152.68	0.205	0.117	0.262	0.047	0.115
Iron and Steel	4,676	160	227.40	0.148	0.088	0.101	0.032	0.056
Leather & Fur	4,852	89	320.70	0.362	0.036	0.682	0.005	0.335
Med, Prec Equip, Clocks	2,702	68	214.89	0.296	0.180	0.457	0.063	0.299
Metal Products	10,686	157	146.93	0.233	0.086	0.332	0.028	0.161
Non-ferrous Metal	3,607	139	157.75	0.186	0.093	0.180	0.035	0.093
Non-metallic Products	15,347	259	195.57	0.207	0.090	0.169	0.059	0.088
Paper	5,698	159	151.05	0.269	0.061	0.127	0.026	0.131
Plastic	9,235	159	140.47	0.298	0.065	0.327	0.019	0.235
Printing	3,382	98	133.01	0.303	0.084	0.118	0.150	0.109
Radio TV PC & Comm	6,699	90	402.04	0.342	0.120	0.571	0.038	0.459
Rubber	2,212	79	226.25	0.294	0.067	0.377	0.027	0.218
Specific Machinery	7,816	167	176.76	0.197	0.154	0.244	0.072	0.166
Textile	18,292	186	222.43	0.390	0.044	0.406	0.018	0.168
Transport Equipment	8,632	168	252.01	0.228	0.120	0.240	0.088	0.138
Wood	3,629	133	137.04	0.288	0.050	0.290	0.025	0.137

D Estimates Referenced in Main Text

D.1 Verisimilitude of Census and Firm Wages

One of the main concerns about combining census data with manufacturing data is the representativeness of regional labor market conditions in determining actual wages within firms. It turns out they are remarkably good predictors of a firm's labor expenses. We construct a predictor of firm wages based on Census data and test it as follows: First, compute the average wages per prefecture. Second, make an estimate CensusWage by multiplying each firm's distribution of workers by the average wages of each type from the population census. Third, regress actual firm wages on CensusWage. The results are presented in Table 13 of

Appendix D.1. Not only is the R^2 of this predictor very high for each industry, but the coefficient on CensusWage is close to one in all cases, showing that one-for-one the census based averages are excellent at explaining the variation in the wage bill across firms.

Table 13: Census Wages as a Predictor of Reported Firm Wages

Industry	Dependent Variable: ln (Firm Wage)					
	ln (Census Wage)	Std Dev	Constant	Std Dev	Obs	R^2
Beverages	1.052***	(0.0147)	-0.904***	(0.204)	2223	0.85
Electrical Equipment	1.018***	(0.0103)	-0.370***	(0.138)	12213	0.86
Food Manufacturing	1.032***	(0.0104)	-0.602***	(0.144)	3766	0.83
General Machinery	1.020***	(0.0063)	-0.365***	(0.091)	15711	0.84
Iron and Steel	1.049***	(0.0082)	-0.777***	(0.116)	4663	0.87
Leather & Fur	0.982***	(0.0112)	0.116	(0.165)	4851	0.87
Med, Prec Equip, Clocks	1.018***	(0.0221)	-0.332	(0.308)	2689	0.83
Metal Products	1.012***	(0.0094)	-0.286**	(0.130)	10654	0.83
Non-ferrous Metal	1.054***	(0.0092)	-0.833***	(0.127)	3588	0.88
Non-metallic Products	0.981***	(0.0085)	0.16	(0.122)	15329	0.80
Paper	1.012***	(0.0086)	-0.335***	(0.120)	5695	0.82
Plastic	1.015***	(0.0129)	-0.340**	(0.170)	9214	0.85
Printing	1.055***	(0.0135)	-0.839***	(0.189)	3377	0.83
Radio TV PC & Comm	1.021***	(0.0172)	-0.354	(0.224)	6685	0.86
Rubber	1.000***	(0.0132)	-0.133	(0.182)	2195	0.87
Specific Machinery	1.036***	(0.0105)	-0.580***	(0.139)	7780	0.83
Textile	0.981***	(0.0060)	0.132	(0.084)	18281	0.86
Transport Equipment	1.050***	(0.0071)	-0.755***	(0.099)	8618	0.86
Wood	0.965***	(0.0136)	0.309	(0.197)	3619	0.78

Standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

D.2 First Stage Results By Industry

Table 14: First Stage Estimates I

Industry	Beverages	Electrical Equip	Food Manuf	General Machinery	Iron & Steel	Leather & Fur	Med, Clocks Prec Equip	Metal Products	Non-ferrous Metal
					Dependent Variable: ln (%type)				
$\ln(w_{R,i})$	-1.808^{a}	-2.977^{a}	-0.870	-2.687^{a}	-2.150^{a}	-0.708^{c}	-4.517^{a}	-3.174^{a}	-3.096^{a}
$\ln(a_{R,i})$	1.673^{a}	1.878^{a}	1.489^{a}	1.794^{a}	1.018^{a}	0.636^{a}	3.358^{a}	1.439^{a}	1.627^{a}
m_1 ($\leq$Junior HS: Fem)	-8.447^{a}	-9.491^{a}	-3.186	-10.170^{a}	7.190^{a}	-2.052	-13.450^{a}	-5.800^{a}	-1.189
m_2 ($\leq$Junior HS: Male)	-5.947^{c}	-7.181^{a}	-1.504	-6.171^{a}	12.370^{a}	-1.089	-11.160^{a}	-2.176^{c}	3.768^{c}
m_3 (Senior High School)	-2.470	-4.475^{a}	1.123	-3.180^{a}	14.210^{a}	-2.058^{c}	-4.100^{b}	-0.758	6.119^{a}
m_1*% Non-Ag Hukou	0.837	-7.619^{a}	-2.341^{b}	-5.957^{a}	-2.373^{c}	-4.544^{a}	-7.142^{a}	-6.038^{a}	-4.591^{a}
m_2*% Non-Ag Hukou	0.306	-3.272^{a}	-1.880	-3.072^{a}	-1.355	-2.882^{c}	-3.957^{c}	-1.805^{b}	-0.370
m_3*% Non-Ag Hukou	-1.102	-0.593	-0.837	-3.218^{a}	-2.394^{a}	-1.606^{b}	0.315	-1.104^{b}	-0.903
m_4*% Non-Ag Hukou	-3.913	-4.572^{a}	-0.426	-7.026^{a}	10.130^{a}	-8.496^{a}	1.793	-2.491^{b}	3.403
$\underline{m}_1 *$ Urban Dummy	-0.271	-1.379^{a}	-1.462^{a}	-1.384^{a}	-1.393^{a}	-0.0822	-1.032^{a}	-1.408^{a}	-1.188^{a}
$\underline{m}_2 *$ Urban Dummy	-0.007	-0.991^{a}	-1.085^{a}	-0.980^{a}	-0.585^{a}	-0.128	-1.176^{a}	-0.533^{a}	-0.601^{a}
$\underline{m}_3 *$ Urban Dummy	0.286^{c}	0.139^{b}	0.175	0.427^{a}	0.503^{a}	0.220^{c}	-0.249	0.247^{a}	0.108
$\underline{m}_4 *$ Urban Dummy	2.212^{a}	1.513^{a}	1.743^{a}	2.336^{a}	3.275^{a}	0.683^{a}	1.053^{a}	2.147^{a}	1.791^{a}
m_1*% Foreign Equity	0.531^{a}	1.030^{a}	0.841^{a}	0.934^{a}	0.751^{a}	-0.107	1.952^{a}	0.876^{a}	1.366^{a}
m_2*% Foreign Equity	0.422^{a}	0.678^{a}	0.661^{a}	0.403^{a}	0.354^{a}	-0.0680	1.840^{a}	0.335^{a}	0.432^{a}
m_3*% Foreign Equity	0.106	0.259^{a}	0.197^{b}	0.143^{a}	0.083	0.257^{a}	0.574^{a}	0.145^{a}	0.093
m_4*% Foreign Equity	-0.005	0.232^{a}	0.015	0.351^{a}	-0.069	0.249	0.033	-0.150	0.589^{a}
$m_1 * \ln(\text{Firm Age})$	-2.803^{a}	-0.215	-0.983^{a}	-2.448^{a}	-2.160^{a}	0.113	0.727^{b}	-0.627^{a}	-2.156^{a}
$m_2 * \ln(\text{Firm Age})$	-2.290^{a}	-0.547^{a}	-0.494^{c}	-1.864^{a}	-1.662^{a}	-0.190^{b}	0.319	-0.788^{a}	-1.838^{a}
$m_3 * \ln(\text{Firm Age})$	0.714^{a}	-0.114	0.016	0.311^{a}	0.862^{a}	0.198	-0.510^{b}	0.417^{a}	0.695^{a}
$m_4 * \ln(\text{Firm Age})$	2.840^{a}	1.621^{a}	2.301^{a}	3.847^{a}	5.656^{a}	3.133^{a}	0.279	3.488^{a}	4.413^{a}
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,900	48,960	15,228	62,908	18,704	19,408	10,808	42,744	14,428
R-squared	0.124	0.117	0.098	0.139	0.168	0.208	0.246	0.124	0.145

Note: a, b and c denote 1, 5 and 10% significance level respectively.

Table 15: First Stage Estimates II

Industry	Other Non-metalllic	Paper	Plastic	Printing	Radio, TV, PC, Comm	Rubber	Specific Machinery	Textile	Transport Equip	Wood
	Dependent Variable: $\ln(\%\text{type})$									
$\ln(w_{R,i})$	-1.693^a	-1.542^a	-3.324^a	-3.491^a	-3.371^a	-0.854	-1.260^a	-2.230^a	-0.372	-1.220^b
$\ln(a_{R,i})$	1.664^a	0.332^b	1.321^a	1.212^a	2.785^a	1.267^a	1.961^a	0.830^a	1.477^a	2.286^a
m_1 ($\leq$Junior HS: Fem)	-7.246^a	-3.469^c	-7.881^a	-5.515^b	-13.770^a	-1.997	-10.130^a	1.588	-6.326^a	-10.890^a
m_2 ($\leq$Junior HS: Male)	-3.128^a	-0.645	-4.596^a	-2.913	-11.970^a	0.188	-4.811^a	2.703^b	-3.359^b	-9.086^a
m_3 (Senior High School)	-0.808	0.076	-2.657^b	-1.849	-7.325^a	2.347	-1.515	3.468^a	-1.290	-6.106^b
m_1*% Non-Ag Hukou	-2.750^a	-6.210^a	-6.682^a	-5.979^a	-7.176^a	-5.162^a	-4.763^a	-6.271^a	-5.279^a	-0.301
m_2*% Non-Ag Hukou	-1.750^a	-6.148^a	-4.710^a	-4.386^a	-5.210^a	-2.819^c	-4.295^a	-5.555^a	-3.153^a	-0.308
m_3*% Non-Ag Hukou	-2.198^a	-3.251^a	-2.685^a	-1.835^b	0.597	-3.361^a	-1.463^a	-3.264^a	-1.039^b	-2.549^a
m_4*% Non-Ag Hukou	-3.926^a	-7.690^a	-7.074^a	-4.440^c	-3.291^a	-2.211	-2.447	-4.025^a	-3.450^b	-13.060^a
$\underline{m}_1 *$ Urban Dummy	-1.333^a	-0.691^a	-1.057^a	-1.711^a	-1.881^a	-0.819^a	-1.597^a	-0.650^a	-1.130^a	-1.630^a
$\underline{m}_2 *$ Urban Dummy	-0.834^a	-0.338^b	-0.590^a	-1.170^a	-1.619^a	-0.603^a	-1.234^a	-0.421^a	-0.714^a	-0.720^a
$\underline{m}_3 *$ Urban Dummy	0.250^a	0.350^a	0.272^a	0.198	-0.512^a	-0.035	0.216^b	0.285^a	0.233^a	0.129
$\underline{m}_4 *$ Urban Dummy	2.570^a	2.644^a	2.413^a	2.251^a	0.902^a	2.211^a	1.924^a	2.709^a	1.381^a	3.331^a
m_1*% Foreign Equity	0.834^a	0.407^a	0.877^a	0.193	1.340^a	0.620^a	1.588^a	0.214^a	1.023^a	0.415^a
m_2*% Foreign Equity	0.244^a	0.153^c	0.361^a	-0.029	1.072^a	0.234^c	0.750^a	0.202^a	0.547^a	0.176
m_3*% Foreign Equity	0.028	0.039	0.048	0.242^a	0.294^a	0.002	0.169^a	0.137^a	0.129^a	-0.142
m_4*% Foreign Equity	-0.310^a	-0.012	0.000	0.176	-0.160^b	-0.191	0.097	0.442^a	0.168^b	0.197
$m_1 * \ln(\text{Firm Age})$	-1.016^a	-1.899^a	-0.857^a	-0.247	0.310	-0.576	-1.601^a	-0.384^a	-1.266^a	-0.423
$m_2 * \ln(\text{Firm Age})$	-0.768^a	-0.819^a	-0.773^a	-0.402	0.223	-0.242	-1.675^a	-0.058	-1.171^a	0.066
$m_3 * \ln(\text{Firm Age})$	0.105	0.457^a	0.398^a	-0.023	-0.049	0.319	0.100	0.445^a	0.588^a	-0.468
$m_4 * \ln(\text{Firm Age})$	3.429^a	4.850^a	3.776^a	3.143^a	0.321^a	2.577^a	1.629^a	4.391^a	2.298^a	3.850^a
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,388	22,792	36,940	13,528	26,796	8,848	31,264	73,168	34,528	14,516
R-squared	0.150	0.164	0.130	0.107	0.188	0.120	0.177	0.221	0.129	0.245

Note: a, b and c denote 1, 5 and 10% significance level respectively.

D.3 First and Second Stage Models Parameter Estimates

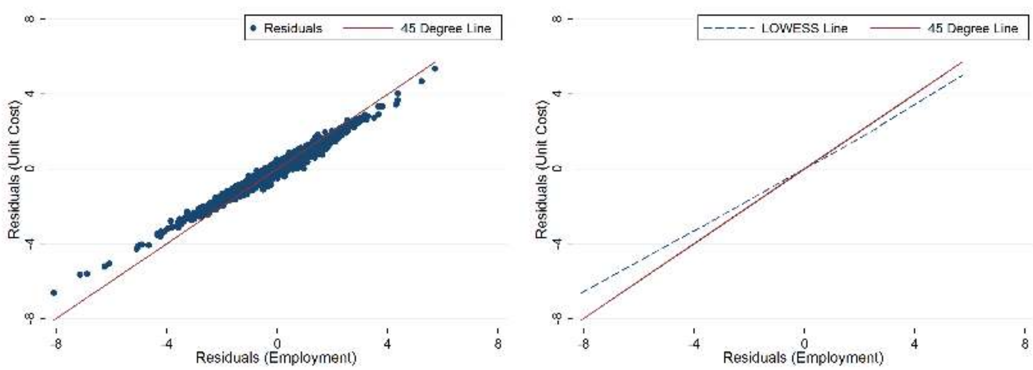
Table 16: Model Primitive Estimates

Industry	k	Std Err	θ	Std Err	β	Std Err	α_L	Std Err	α_K	Std Err	α_M	Std Err
Beverages	2.12	(0.38)	1.24	(0.08)	0.75	(0.08)	0.13	(.05)	0.10	(.007)	0.70	(.04)
Electrical Equipment	2.60	(0.15)	1.22	(0.02)	0.65	(0.03)	0.25	(.01)	0.14	(.001)	0.47	(.00)
Food Manufacturing	1.59	(0.36)	1.28	(0.13)	0.86	(0.10)	0.14	(.08)	0.09	(.009)	0.70	(.06)
General Machinery	2.50	(0.14)	1.22	(0.03)	0.68	(0.03)	0.17	(.02)	0.12	(.003)	0.60	(.01)
Iron and Steel	3.21	(0.56)	1.00	(0.06)	1.02	(0.15)	0.40	(.06)	0.07	(.010)	0.48	(.05)
Leather & Fur	2.15	(0.70)	0.76	(0.14)	1.24	(0.24)	0.10	(.11)	0.13	(.017)	0.59	(.07)
Med, Prec Equip, Clocks	2.34	(0.18)	1.43	(0.05)	0.43	(0.03)	0.20	(.01)	0.16	(.003)	0.43	(.01)
Metal Products	3.20	(0.24)	1.10	(0.03)	0.77	(0.05)	0.24	(.01)	0.14	(.001)	0.46	(.00)
Non-ferrous Metal	2.89	(0.38)	1.15	(0.05)	0.72	(0.08)	0.40	(.03)	0.08	(.005)	0.43	(.02)
Non-metallic Products	2.02	(0.16)	1.25	(0.04)	0.75	(0.03)	0.20	(.02)	0.07	(.002)	0.61	(.02)
Paper	6.25	(3.82)	0.73	(0.11)	2.48	(2.08)	0.18	(.36)	0.14	(.026)	0.53	(.28)
Plastic	3.51	(0.29)	1.08	(0.03)	0.81	(0.06)	0.27	(.04)	0.14	(.008)	0.41	(.02)
Printing	3.93	(0.60)	1.04	(0.04)	0.89	(0.12)	0.09	(.06)	0.22	(.014)	0.55	(.03)
Radio TV PC & Comm	2.21	(0.14)	1.41	(0.04)	0.51	(0.03)	0.16	(.01)	0.21	(.003)	0.43	(.01)
Rubber	1.63	(0.61)	1.15	(0.19)	0.93	(0.17)	0.06	(.15)	0.13	(.021)	0.63	(.10)
Specific Machinery	1.63	(0.18)	1.43	(0.07)	0.74	(0.05)	0.10	(.03)	0.16	(.005)	0.55	(.02)
Textile	3.73	(0.36)	0.95	(0.03)	1.15	(0.09)	0.12	(.05)	0.11	(.007)	0.61	(.03)
Transport Equipment	1.26	(0.24)	1.38	(0.13)	0.92	(0.09)	0.04	(.03)	0.15	(.006)	0.65	(.02)
Wood	1.52	(0.22)	1.62	(0.17)	0.71	(0.09)	0.22	(.11)	0.10	(.017)	0.56	(.08)

D.4 Residual Comparison: Unit Labor Costs vs Substitutable Labor

Of particular interest for work on productivity are the residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity. Figure D.1 contrasts the results of our method with the result when total employment is used as a measure of labor. Examining the 45 degree line also plotted in the Figure, a general pattern emerges: above average firms under the employment measure are slightly less productive under the unit cost approach, while below average firms are more productive. This suggests that a more detailed analysis of the role of local factor markets may substantially alter interpretation of differences in firm productivity.

Figure D.1: Productivity: Unit Labor Costs vs Total Employment (General Machinery)



D.5 Firm Performance Characteristics and Productivity

Table 17: Explaining Growth with Productivity

	Sales Growth Rate (2005-7)		
Productivity under Unit Cost method	-0.074**		
	(0.030)		
Productivity under L =Employment		-0.052**	
		(0.021)	
Productivity under L =Wage Bill			-0.054**
			(0.022)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	119,159	119,159	119,159
R-squared	0.027	0.027	0.027

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

Table 18: Explaining Propensity to Export with Productivity

	Export Dummy (2005)		
Productivity under Unit Cost method	0.024***		
	(0.007)		
Productivity under L =Employment		0.015***	
		(0.004)	
Productivity under L =Wage Bill			0.017***
			(0.004)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.202	0.202	0.202

Standard errors in parentheses. Significance: *** p<.01, ** p<.05, * p<.1.

E Supplemental Appendix

E.1 Derivation of Region-Techonology Budget Shares

Using the profit maximizing price P_{Rj}^{T} and combining Equations (2.12), (3.1) and (3.2) then yields the equilibrium quantity produced,

$$Q_{Rj}^{T} = \rho I_{\text{Agg}} \left(u_R^T \eta_j \left(U_R^T / \sigma_R^T \right)^{1/\rho} \right)^{\rho/(\rho-1)} / u_{Rj}^T \sum_{t,r} \left(\sigma_r^t \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{E.1}$$

Aggregating revenues using Equation (E.1) shows that each consumer's budget share allocated to region R and industry T is

$$\text{Consumer Budget Share for R, T}: \quad \left(\sigma_R^T \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \tag{E.2}$$

Consequently, since free entry implies expected profits must equal expected fixed costs, the mass of entrants $\mathbb{M}_R^T$ solves the implicit form[24]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right) = \mathbb{M}_R^T u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e \right), \quad \text{(E.3)}$$

while the equilibrium cost cutoffs $\overline{\eta}_R^T$ solve the zero profit condition[25]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\sigma_R^T\right)^{1/(1-\rho)} \left(u_R^T \overline{\eta}_R^T \left(U_R^T\right)^{1/\rho} \right)^{\rho/(\rho-1)} = u_R^T f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t. \quad \text{(E.4)}$$

Equations (E.3) and (E.4) fix $\overline{\eta}_R^T$ since combining them shows

$$\int_0^{\overline{\eta}_R^T} \left(\eta_{Rz}^T / \overline{\eta}_R^T\right)^{\rho/(\rho-1)} dG(z) / G\left(\overline{\eta}_R^T\right) = 1 + F_e / f_e G\left(\overline{\eta}_R^T\right).$$

In particular, $\overline{\eta}_R^T$ does not vary by region or technology. Thus, Equation (E.4) shows that

$$U_R^T u_R^T / \sigma_R^T = \left[(1-\rho) I_{\text{Agg}} / \rho f_e \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right]^{1-\rho} / \left(\overline{\eta}_R^T\right)^{\rho}. \quad \text{(E.5)}$$

where the RHS does not vary by region or technology. Combining this equation with (3.2) shows $Q_{Rj}^T = Q_{R'j}^{T'}$ for all (T,R) and (T',R'), so that $\mathbb{M}_R^T u_R^T / \sigma_R^T = \mathbb{M}_{R'}^{T'} u_{R'}^{T'} / \sigma_{R'}^{T'}$. At the same time, using Equation (E.5) reduces (E.2) to

$$\text{Consumer Budget Share for R, T:} \quad \mathbb{M}_R^T u_R^T / \sum_{t,r} \mathbb{M}_r^t u_t^t = \sigma_R^T / \sum_{t,r} \sigma_r^t = \sigma_R^T.$$

Since $\sum_{t,r} \sigma_r^t = 1$, each region and industry receive a share σ_R^T of consumer expenditure.

[24] To see a solution exists, note that for fixed prices, $\left\{\widetilde{\eta}_R^T\right\}$, and $\left\{\overline{\eta}_R^T\right\}$, necessarily $\mathbb{M}_R^T \in A_R^T \equiv \left[0, (1-\rho) I_{\text{Agg}} / \rho u_R^T F_e\right]$. Existence follows from the Brouwer fixed point theorem on the domain $\times_{R,T} A_R^T$ for $H\left(\left\{\widetilde{\mathbb{M}}_R^T\right\}\right) \equiv (1-\rho) I_{\text{Agg}} \left(\left(\sigma_R^T\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_R^T \widetilde{\eta}_R^T / \sum_{t,r} \left(\sigma_r^t\right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_r^t \widetilde{\eta}_r^t \right) / \rho u_R^T \left(f_e G\left(\overline{\eta}_R^T\right) + F_e \right)$.

[25] To see a solution exists, note that for fixed prices, $\left\{\mathbb{M}_{R'}^{T'}\right\}$ and $\left\{U_R^T\right\}$, the LHS ranges from 0 to ∞ as $\overline{\eta}_R^T$ varies, while the RHS is bounded away from 0 and ∞ when $\min\left\{\widetilde{\eta}_r^t G\left(\overline{\eta}_r^t\right)\right\} > 0$. $\widetilde{\eta}_R^T G\left(\overline{\eta}_R^T\right) > 0$ follows from inada type conditions on goods from each T and R.

E.2 Regional Variation in Input Use

Equation (4.1) specifies the relative shares of each type of worker hired. Since input markets are competitive, firms and workers take regional labor market characteristics as given. As characteristics such as wages worker availability and human capital vary, the share of each labor type hired differs across regions. These differences can be broken up into direct and indirect effects. Direct effects ignore substitution by holding the unit labor cost $\widetilde{c}_{RT}$ constant, while indirect effects measure how regional differences give rise to substitution. The direct effects are easy to read off of Equation (4.1), showing:

$$\begin{aligned}\text{Direct Effects}: \quad & d\ln s_{R,T,i}/d\ln w_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = -k/\beta^T \ < 0, && \text{(E.6)}\\ & d\ln s_{R,T,i}/d\ln a_{R,i}|_{\widetilde{c}_{RT}\text{ constant}} = \theta^T/\beta^T \ > 0, && \text{(E.7)}\\ & d\ln s_{R,T,i}/d\ln \underline{m}_i^T|_{\widetilde{c}_{RT}\text{ constant}} = k\theta^T/\beta^T > 0. && \text{(E.8)}\end{aligned}$$

These direct effects have the obvious signs: higher wages ($w_{R,i}\uparrow$) discourage hiring a particular type while greater availability ($a_{R,i}\uparrow$) and higher human capital ($m_{T,i}\uparrow$) encourage hiring that type. The indirect effects of substitution through $\widetilde{c}_{RT}$ are less obvious as seen by

$$\begin{aligned} d\ln\widetilde{c}_{RT}^k/d\ln w_{R,i} &= \left(k/\theta^T\right)\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T}\widetilde{c}_{RT}^{k\left(\theta^T/\beta^T\right)} > 0, && \text{(E.9)}\\ d\ln\widetilde{c}_{RT}^k/d\ln a_{R,i} &= -\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T}\widetilde{c}_{RT}^{k\left(\theta^T/\beta^T\right)} < 0, && \text{(E.10)}\\ d\ln\widetilde{c}_{RT}^k/d\ln \underline{m}_i^T &= -k\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T}\widetilde{c}_{RT}^{k\left(\theta^T/\beta^T\right)} < 0. && \text{(E.11)}\end{aligned}$$

Thus, the indirect effects counteract the direct effects through substitution. To see the total of the direct and indirect effects, define the Type-Region-Technology coefficients $\chi_{i,R,T}$:

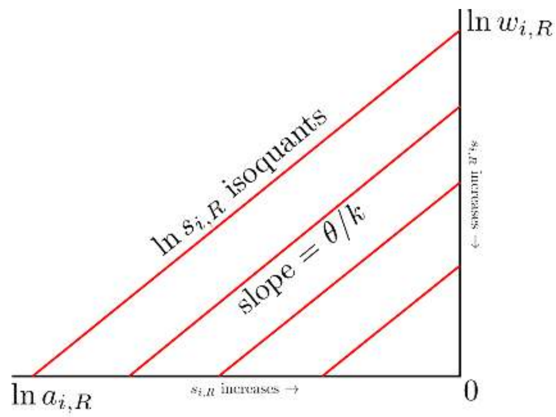
$$\chi_{i,R,T} \equiv 1-\left[a_{R,i}\left(\underline{m}_i^T\right)^k w_{R,i}^{1-k-\beta^T/\theta^T}\right]^{\theta^T/\beta^T}\widetilde{c}_{RT}^{k\left(\theta^T/\beta^T\right)}.$$

Investigation shows that each $\chi_{i,R,T}$ is between zero and one. Combining Equations (E.6-E.8) and Equations (E.9-E.11) shows that the direct effect dominates since

$$\begin{aligned}\text{Total Effects}: \quad & d\ln s_{R,T,i}/d\ln w_{R,i} = \left[-k/\beta^T\right]\chi_{i,R,T} \ < 0, && \text{(E.12)}\\ & d\ln s_{R,T,i}/d\ln a_{R,i} = \left[\theta^T/\beta^T\right]\chi_{i,R,T} \ > 0, && \text{(E.13)}\\ & d\ln s_{R,T,i}/d\ln \underline{m}_i^T = \left[k\theta^T/\beta^T\right]\chi_{i,R,T} > 0. && \text{(E.14)}\end{aligned}$$

Equations (E.12-E.14) summarize the relationship between regions and labor market characteristics in a parsimonious way. For small changes in labor market characteristics, the log share of a type hired in linear in log characteristics with a slope determined by model parameters and a regional shifter $\chi_{i,R,T}$. These (local) isoquants for the share of type i workers hired in region R are depicted in Figure E.1.

Figure E.1: Local isoquants for Share of Workers Hired



E.3 Regional Variation in Theory: Isoquants

Equations (E.12-E.14) also characterize local isoquants of hiring the same share of a type across regions. It is immediate that for small changes in market characteristics, $\begin{pmatrix} \Delta_w, & \Delta_a, & \Delta_m \end{pmatrix}$, the share of a type hired is constant so long as

$$-\left(k/\theta^T\right)\Delta_w/w_{R,i}+\Delta_a/a_{R,i}+k\Delta_m/\underline{m}_i^T=0.$$

For instance, firms in regions R and R' will hire the same fraction of type i workers for small differences in characteristics (Δ_w,Δ_a) so long as

$$\Delta_w/\Delta_a=\left(\theta^T/k\right)w_{R,i}/a_{R,i}. \tag{E.15}$$

By itself, an increase in type i wages Δ_w would cause firms to hire a lower share of type i workers as indicated by the direct effect. However, Equation (E.15) shows that firms would keep the same share of type i workers if the availability Δ_a increases concurrently so that Equation (E.15) holds.

E.4 Derivation of Unit Labor Costs

Unit labor costs by definition solve

$$\text{Unit Labor Costs}: \quad c_R^T \equiv \min_H C_T\left(H|a_R, w_R\right) \text{ subject to } L = \phi\left(\tilde{H}, \theta^T\right) \cdot H_{\text{TOT}} = 1.$$

Under the parameterization $\Psi(h) = 1 - h^{-k}$, Equations (2.2) become

$$H_i = a_{R,i}k/(k-1) \cdot \underline{m}_i^T \underline{h}_i^{1-k} \cdot N. \tag{E.16}$$

From above, $w_{R,i}H_i/\underline{m}_i^T \underline{h}_i C_T\left(H|a_R, w_R\right) = H_i^{\theta^T}/\sum_j H_j^{\theta^T}$, and $L = 1 = \left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T}$ so

$$\underline{h}_i = w_{R,i}H_i^{1-\theta^T}/\underline{m}_i^T C_T\left(H|a_R, w_R\right). \tag{E.17}$$

Substitution now yields

$$H_i = a_{R,i}k/(k-1) \cdot \underline{m}_i^T \left(w_{R,i}H_i^{1-\theta^T}/\underline{m}_i^T C_T\left(H|a_R, w_R\right)\right)^{1-k} \cdot N. \tag{E.18}$$

Further reduction and the definition of β^T shows that

$$H_i^{\beta^T} = H_i^{\theta^T+k-k\theta^T} = a_{R,i}k/(k-1) \cdot \left(\underline{m}_i^T\right)^k w_{R,i}^{1-k} C_T\left(H|a_R, w_R\right)^{k-1} N. \tag{E.19}$$

Again using $\left(\sum_j H_j^{\theta^T}\right)^{1/\theta^T} = 1$ then shows

$$1 = \sum_i \left[a_{R,i}k/(k-1) \cdot \underline{m}_i^{Tk} w_{R,i}^{1-k}\left(c_R^T\right)^{k-1} N\right]^{\theta^T/\beta^T}. \tag{E.20}$$

From the definition of the cost function we have

$$c_R^T = N\left[\sum_i a_{R,i}w_{R,i}\underline{h}_i^{-k} + fc_R^T\right] = \sum_i w_{R,i}\left((k-1)/k\right)H_i/\underline{m}_i^T \underline{h}_i + Nfc_R^T.$$

Therefore from $w_{R,i}H_i/\underline{m}_i^T \underline{h}_i C_T\left(H|a_R, w_R\right) = H_i^{\theta^T}$ it follows

$$1 = \sum_i (k-1)/k \cdot H_i^{\theta^T} + Nf = (k-1)/k + Nf,$$

and therefore $N = 1/fk$. Now from Equation (E.20) c_R^T is seen to be Equation (2.10).

E.5 Derivation of Employment Shares

Combining Equations (E.17), (E.19) and $N = 1/fk$ shows

$$\underline{h}_i = a_{R,i}^{(1-\theta^T)/\beta^T} \left(\underline{m}_i^T\right)^{-\theta^T/\beta^T} w_{R,i}^{1/\beta^T} \left(c_R^T\right)^{-1/\beta^T} / \left(f\left(k-1\right)\right)^{(1-\theta^T)/\beta^T}. \tag{E.21}$$

Let $A_{R,i}^T$ be the number of type i workers hired to make $L = 1$, exclusive of fixed search costs. By definition, $A_{R,i}^T = N|_{L=1}\, a_{R,i}\left(1 - \Psi\left(\underline{h}_i\right)\right) = a_{R,i}\underline{h}_i^{-k}/fk$. Using Equation (E.21),

$$A_{R,i}^T = k^{-1}\left(k-1\right) a_{R,i}^{\theta^T/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(c_R^T\right)^{k/\beta^T} \left(k-1\right)^{-\theta^T/\beta^T} f^{-1}.$$

Labor is also consumed by the fixed search costs which consist of $N|_{L=1} \cdot f = 1/k$ labor units. Therefore, if $\widetilde{A}_{R,i}^T$ denotes the total number of type i workers hired to make $L = 1$, necessarily $\widetilde{A}_{R,i}^T = A_{R,i}^T + \widetilde{A}_{R,i}^T/k$ so $\widetilde{A}_{R,i}^T = k\left(k-1\right)^{-1} A_{R,i}^T$, and the total number of type i workers hired in region R using technology T is $L_R^T \widetilde{A}_{R,i}^T$. The total number of employees in R, T is $\sum_i L_R^T \widetilde{A}_{R,i}^T = L_R^T \left(c_R^T\right)^{k/\beta^T} \left(\widetilde{c}_R^T\right)^{-k\theta^T/\beta^T}$, where $\widetilde{c}_R^T$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$[26].

[26] Formally $\tilde{c}_R^T \equiv \min_H C_T\left(H | a_R, \left\{w_{R,i}^{-k/\theta^T(1-k)}\right\}\right)$ subject to $L = \phi\left(\tilde{H}, \theta^T\right) \cdot H_{\text{TOT}} = 1$.