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

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Abstract

Although firms are dispersed across space and may face radically different production conditions, this dimension of firm heterogeneity is often overlooked. Differences between factor markets, especially for labor, are stark. To pursue this line of inquiry, we model firm hiring across local labor markets. We then use the model to estimate and quantify the role of distinct regional labor markets in firm input use, productivity and location by combining firm and population census data. Considering modern China as a country with substantial regional variation, we find labor costs vary by 30-80%, leading to 3-17% differences in total factor productivity once non-labor inputs are considered. Favorably endowed regions attract more value added per capita, providing new insights into within-country comparative advantage and specialization.

JEL classifications: D5, F1, J3, O1

Keywords: General Equilibrium, Factor Endowments, Structural Estimation, Productivity

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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. Modelling firm adaptation to different factor markets provides 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.[2] 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, productivity and location.

Although there might be many complementary ways to address our question, we take an approach rooted in the general equilibrium trade literature to understand how local endowments impact firms which enter endogenously, as typified by Bernard et al. (2007). We extend their model to incorporate entry across regional markets and richer employment structures. Each region is endowed with a different distribution of skill types and wages across workers. Industries vary in team technology, which is their ability to substitute between different types of labor (e.g. Bowles, 1970). Firms hire teams of workers by choosing the optimal combination of workers given local conditions. Since each firm's optimal labor force varies by industry technology and region, the comparative suitability of regions varies by industry. Firms thus locate in proportion to the cost advantages available.

In the model, finding new employees entails fixed costs and the ease of finding any type of worker increases with their regional supply. Therefore firm hiring depends on the joint distribution of worker types and wages. Since labor demand depends on technology and regional labor markets, this implies effective labor costs vary by region and industry. These labor costs help explain differences in productivity.[3] But are these differences economically important? To quantify real world supply conditions, we use the model to derive estimating equations which fix: 1) hiring by wage and worker type distributions, 2) substitution into

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

[2] Institutional mobility constraints, such as the *hukou* system in China, likely further exacerbate differences.

[3] 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'.

non-labor inputs, and 3) firm location in response to local factor markets.

The estimation strategy combines manufacturing and population census data for China in the mid-2000s, a setting which exhibits substantial variation in labor market conditions. By revealing how firm demand for skills varies with local conditions, the model allows recovery of the unit costs for labor across China. Our estimates imply an interquartile difference in effective labor costs of 30 to 80 percent. A second stage estimates production functions, explicitly accounting for regional cost differences. Since firms are capable of substituting into non-labor inputs, productivity differences are smaller than labor cost differences. Once substitution is accounted for, labor costs result in firm productivity differences of 3 to 17 percent, and explain 4 to 43 percent of the variance of productivity.[4] Furthermore, we show that economic activity locates where regional costs are lowest, as implied by the model.

We conclude this section by relating the paper to existing work. The paper then 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 the determination of factor prices and firm location. Section 4 explains how the model can be estimated with a simple nested OLS approach. 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.

Our consideration of firms as dependent on local factor markets is based on models typified by the Heckscher-Ohlin-Vanek theory of international trade (e.g. Vanek, 1968). The departures from H-O-V in our model relax assumptions about perfect labor substitutability and homogeneous factor markets, which quantifies the role of local labor markets. On the product market side, we consider many goods as indicated by Bernstein and Weinstein (2002) as appropriate when considering the locational role of factor endowments. We follow a multi-sector approach similar to Melitz (2003), but add free entry by firms across regions. A firm's optimal location depends on local costs which arise from the regional distribution of worker types and wages, but competition from firms which enter the same region prevent complete specialization. The model quantifies the intensity of firm entry and shows that within country, advantageous local factor markets are important for understanding specialization patterns.[5]

Recently, both Borjas (2009) and Ottaviano and Peri (2010) have emphasized the importance of more complete model frameworks to estimate substitution between worker types. In distinction to the labor literature, our interest is firm substitution across factor markets. Dovetailing with this are theories proposing that different industries perform optimally under

[4] These substantial differences underscore 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.

[5] In spirit, this result is akin to Fitzgerald and Hallak (2004) who study the role of cross country productivity differences in specialization. In our case, differences in unit labor costs predict specialization across regions.

different degrees of skill diversity. 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) models multiple industries and general skill distributions, and finds that skill diversity is explains productivity and export differences in developing countries.

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 labor markets and agglomeration economies, explicitly modelling 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 on effective labor costs and firm location.[6,7]

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 et al. (2008) find that higher skill dispersion is associated with higher TFP in Italy. Similarly, Parrotta et al. (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 et al. (2012) 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, 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 through the availability of inputs at the micro level.[8]

Clearly this study also contributes to the empirical literature on Chinese productivity. Ma et al. (2012) show that exporting is positively correlated with TFP and that firms self select into exporting which, ex post, further increases TFP. Brandt et al. (2012) 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

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

[7]Determinants of productivity include market structure (Syverson (2004)), product market rivalry and technology spillovers (Bloom et al. (2007)) and vertical integration (Hortasu and Syverson (2007), Atalay et al. (2012)).

[8]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).

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.[9]

2 The Role of Skill Mix in Production

This section develops a model of hiring in which firms respond to both the wages and quantities of locally available worker types. Firms combine homogeneous inputs (materials, capital) and differentiated inputs (types of labor). While homogeneous inputs are perfectly mobile within industries, we take the distribution of labor endowments as given. Special cases of our model would include perfect factor mobility (equal endowments in all regions) or high migration costs (equalization up to mobility costs). Industries have different technologies available for combining types of labor into teams. We proceed with a detailed specification of the labor hiring process, solving for firms' optimal responses to local labor market supply conditions. This quantifies the unit cost for labor by region in terms of observable local conditions and model parameters.

2.1 Firm Production

Firms within an industry T face a neoclassical production technology $F^T(M, K, L)$ which combines materials M, capital K and labor L to produce output. 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 price r_M^T. While M and K are composed of homogeneous units, effective labor L is produced by combining heterogeneous worker types.

There are $\mathbb{S}$ skill types of workers which are distributed unequally across regions R. The distribution of worker types in region R is denoted $a_R = (a_{R,1}, \ldots, a_{R,\mathbb{S}})$. The regional wages for each type are take as exogenous by workers and firms, and in equilibrium are denote $w_R = (w_{R,1}, \ldots, w_{R,\mathbb{S}})$. Workers do not contribute equally to output. This occurs for two reasons. First, each type provides an industry specific level of human capital $\underline{m}_i^T$. Second, when a worker meets a firm, this match has a random quality $h \geq 1$ which follows a Pareto distribution, $\Psi(h) \equiv 1 - h^{-k}$.

In order to hire workers, a firm must pay a fixed search cost of f effective labor units, at which point they may hire from a distribution of worker types a_R. The firm hires on the basis of match quality, and consequently 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

[9]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).

[10]This assumption is familiar from labor search models (see Helpman et al. (2010)). Unlike Helpman, et al., here differences in hiring patterns are determined by local market conditions.

firm may 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

$$H_i \equiv N \cdot a_{R,i} \underline{m}_i^T \int_{\underline{h}_i}^{\infty} h d\Psi. \tag{2.1}$$

From a firm's perspective, the threshold of worker match quality $\underline{h}$ is a means to choose an optimal level of H. 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 $\underline{h}_i \geq 1$ and to increase N to search harder for suitable workers.

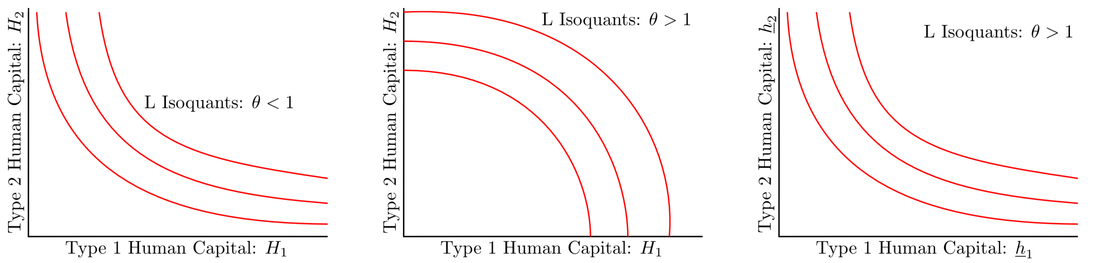
The amount of L produced by the firm depends on the composition of a team through a technological parameter θ^T in the following way:

$$L \equiv \left(H_1^{\theta^T} + H_2^{\theta^T} + \ldots + H_{\mathbb{S}}^{\theta^T} \right)^{1/\theta^T}. \tag{2.2}$$

Notice that in the case of $\theta^T = 1$, this specification collapses to a model where L is the total level of human capital $\sum H_i$. 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 convex in the input of each single type (Figure 2.1b).[11] Below, we show 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 2.1c. This avoids the possibility that some worker types are never hired, in line with real world data patterns.

Figure 2.1: Human Capital Isoquants

(a) Supermodular Production in H (b) Submodular Production in H (c) Submodular Production in $\underline{h}$



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 modelling these disparate markets emphasizes

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

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 Unit Labor Costs by Region and Technology

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, labelled 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

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

To produce a given vector $(H_1,\ldots,H_{\mathbb{S}})$, 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 $\underline{h}$. Alternatively, the firm might save on interviewing costs f by choosing a low number of prospectives N and permissively low values for $\underline{h}$. Local trade offs and the dependence 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

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

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 choice of N implies

$$C^T\left(H|a_R,w_R\right)=\sum_i \mu_i H_i = N\sum w_{R,i}a_{R,i}\int_{\underline{h}_i}^{\infty} h/\underline{h}_i d\Psi. \tag{2.5}$$

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 cost function C^T implies the unit labor cost of L in region R is

$$\text{Unit Labor Cost Problem}: \quad c_R^T \equiv \min_H C^T\left(H|a_R,w_R\right) \text{ subject to } L=1. \tag{2.6}$$

The unit labor cost function may be solved as

$$\text{Unit Labor Costs}: \quad c_R^T = \left[\sum_{i \text{ hired}} \left[a_{R,i} \left(\underline{m}_i^T \right)^k w_{R,i}^{1-k} / f\,(k-1) \right]^{\theta^T/\beta^T} \right]^{\left(\beta^T/\theta^T\right)/(1-k)}. \tag{2.7}$$

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:

$$\sum_i a_{R,i} w_{R,i} \int_{\underline{h}_i}^{\infty} \left(h - \underline{h}_i\right) / \underline{h}_i d\Psi = f c_R^T. \tag{2.8}$$

The LHS of Equation (2.8) 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.[12]

2.3 Optimal Hiring Patterns

The above reasoning shows the relationship between technology and the optimal choice of worker types. It is intuitive that if the right tail of the match quality distribution is sufficiently thick, there are a few excellent matches for each type of worker, so all types are hired.[13] Since match quality follows a Pareto distribution with shape parameter k, expected match quality is $\mathrm{E}[h] = k/(k-1)$. As $k \to 1$ match quality increases, so for k sufficiently close to one, all worker types should be hired. To be precise, a sufficient condition for a firm to optimally hire every type of worker, stated as Proposition 1, is that

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

This clearly holds for $\theta^T \leq 1$, and for $\theta^T > 1$, the condition is equivalent to $k < \theta^T / \left(\theta^T - 1\right)$. This induces the isoquants depicted in Figure 2.1c, 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 $\underline{h}$.

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

[12] The number of times a firm goes to hire workers, N, can be solved as $N = 1/fk$. Thus, N is decreasing in both hiring costs and k. Increases in k imply lower match quality, so that repeatedly screening workers has lower returns.

[13] This is important, not only for the analytical convenience of avoiding complete specialization in the hiring of worker types, but also because we find that each region-industry combination hires all types of workers in our data.

See Appendix. Thus, for $\beta^T > 0$, all worker types are hired. The optimal share of workers of type i hired by firm j under technology T in region R, labeled $s^T_{R,ij}$, is fixed by (2.6):[14]

$$s^T_{R,ij} = a_{R,i}^{\theta^T/\beta^T} w_{R,i}^{-k/\beta^T} \left(\underline{m}_i^T\right)^{k\theta^T/\beta^T} \left(\widetilde{c}_R^T\right)^{\theta^T k/\beta^T} \left(f\left(k-1\right)\right)^{-\theta^T/\beta^T}. \tag{2.9}$$

where $\widetilde{c}_R^T$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$.[15] Notice that in (2.6) , unlike most production models, the factor prices w_R are not sufficient to determine the factor shares a firm will buy. The availability of workers a_R is crucial in determining shares hired because costly search makes firms sensitive to the local supply of each worker type.

2.4 Unit Costs: The Role of Substitution

Equation (2.7) 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. In order to solve for total unit costs (which include non-labor costs), we assume each production function F^T is of a Cobb-Douglas form with constant returns to scale:

$$F^T\left(M,K,L\right) = M^{\alpha_M^T} K^{\alpha_K^T} L^{\alpha_L^T}. \tag{2.10}$$

It is then straightforward to derive total unit costs from (2.7) and (2.10) as

$$\text{Total Unit Costs}: \quad u_R^T = \left(r_M^T/\alpha_M^T\right)^{\alpha_M^T} \left(r_K^T/\alpha_K^T\right)^{\alpha_K^T} \left(c_R^T/\alpha_L^T\right)^{\alpha_L^T}, \tag{2.11}$$

where u_R^T represents the regional component of unit costs for industry T in region R. Within an industry, productivity then varies across regions as in the following example: if firm 1 in region R and firm 2 in region R' face unit labor costs of c_R^T and $c_{R'}^T$ and have the same wage bill W, they will employ labor of $L^1 = W/c_R^T$ and $L^2 = W/c_{R'}^T$. Thus, if these firms hire the same capital and material inputs (K, M), then the ratio of their output is

$$Y^1/Y^2 = \left(M^{\alpha_M^T} K^{\alpha_K^T} L_1^{\alpha_L^T}\right) / \left(M^{\alpha_M^T} K^{\alpha_K^T} L_2^{\alpha_L^T}\right) = \left(L_1/L_2\right)^{\alpha_L^T} = \left(c_{R'}^T/c_R^T\right)^{\alpha_L^T}.$$

Industry differences in productivity therefore depend on 1) the ratio of regional labor costs and 2) the intensity α_L^T of labor in production. Estimating both allows quantification of regional productivity differences. However, we first resolve factor prices and firm location in general equilibrium.

[14] See Supplemental Appendix.

[15] 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 $L = 1$.

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 competition present from other firms who enter the region. We characterize production and location choices conditional on local labor markets. Most strikingly, lower regional production costs attract more firms for any given technology, which determines the intensity of economic activity. Furthermore, we show an equilibrium wage vector exists which supports these choices by firms for any distribution of labor endowments. Thus, endowment distributions as implied by complete labor mobility or migration models are consistent with our framework.

3.1 Firms and Consumers

Each region R is endowed with a population $\mathbb{P}_R$ composed of $\mathbb{S}$ worker types. Firms may enter any region R by paying a sunk entry cost F_e. Firms then receive a random cost draw $\eta_j \sim G$ and face a fixed production cost f_e.[16] Akin to Bernard et al. (2007), firms combine different types of inputs to produce. Each firm j produces a distinct variety, and in equilibrium a mass of firms $\mathbb{M}_R^T$ enter. 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.

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

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

in each region and industry, with total utility $U\left(\mathbb{M}, \overline{\eta}, Q\right) \equiv \Pi_T \Pi_R \left(U_R^T\right)^{\sigma_R^T}$, where σ_R^T are relative weights put on final goods normalized so that $\sum_{T,R} \sigma_R^T = 1$. As shown in the Appendix, each σ_R^T has the usual interpretation as the share of income spent on goods from each region and technology pair (R, T).[17]

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:

$$Q_{Rj}^T = I \cdot \left(P_{Rj}^T U_R^T / \sigma_R^T\right)^{\frac{1}{\rho-1}} / \sum_{t,r} \left(\sigma_r^t\right)^{\frac{1}{\rho-1}} \mathbb{M}_r^t \int_0^{\overline{\eta}_r^t} \left(\left(P_{r,z}^t\right)^\rho U_r^t\right)^{\frac{1}{\rho-1}} dG\left(z\right). \tag{3.1}$$

Clearly, even if consumers have different incomes, aggregate demand for variety j corresponds

[16] This follows Melitz (2003). G is assumed to be absolutely continuous with finite mean.

[17] Note that since the demand for goods from each (R, T) pair enter preferences multiplicatively, complete specialization cannot occur which considerably simplifies the analysis.

to that of a representative consumer with income equal to aggregate income, I_{Agg}. Since labor is supplied inelastically, I_{Agg} is necessarily

$$I_{\text{Agg}} = \sum_R \sum_i \underbrace{w_{R,i} a_{R,i} \mathbb{P}_R}_{\text{Total Wages of Type i in R}} + \sum_T \underbrace{r_M^T M^T + r_K^T K^T}_{\text{Non-labor Income}}. \tag{3.2}$$

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_R^T. Firms maximize profits

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

by choosing an optimal price $P_{Rj}^T = u_R^T \eta_j / \rho$, 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

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

It is shown in the Appendix that the cutoff cost draw $\overline{\eta}_R^T$ depends only on f_e, F_e, and G, so there is a unique cutoff cost that does not vary by region or industry. Having determined firm behavior in the product market, we now examine input markets.

3.2 Regional Factor Market Clearing

The remaining equilibrium conditions are that input prices guarantee firm input demand exhausts materials, capital stocks, and each regional pool of workers. To fix expenditure, we assume each budget share σ_R^T is proportional to $\mathbb{P}_R$, so that $\sigma_R^T = \sigma^T \mathbb{P}_R$ for some σ^T.[18] 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, 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,

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

[18]This assumption is justified by the implication that two regions which have identical skill distributions have the same wage schedule.

Embedded in each L_R^T is the set of workers hired by firms attendant to regional market conditions. The total demand for employees of each type in region R implied by Equation (2.9) must equal the supply of $a_{R,i}\mathbb{P}_R$, yielding the regional resource clearing conditions. Wages are therefore determined by

$$a_{R,i}w_{R,i} = \sum_T \underbrace{\sigma^T}_{\text{Industry Share Per Capita}} \cdot \underbrace{\alpha_L^T}_{\text{Labor Share}} \cdot \underbrace{H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T}}_{\text{Type Share}} \cdot I_{\text{Agg}} \quad \forall R, i. \tag{3.5}$$

Equation (3.5) shows that type i's contribution to mean wages, $a_{R,i}w_{R,i}$, is the sum over income spent an industry, times labor's share, times the wages attributable to each type.[19]

Solving Equation (3.5) requires finding a wage for each worker type in each region that fully employs all workers. To do so, first note that the resource clearing conditions determine wages, provided an exogenous vector of unit labor costs $\{c_R^T\}$, proved in the Appendix: There is a wage function $\mathbb{W}$ that uniquely solves (3.5) 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:

$$\{w_{R,i}\} \underset{\text{Equation 2.7}}{\mapsto} \left\{c_R^T\left(\{w_{R,i}\}\right)\right\} \underset{\text{Lemma}}{\mapsto} \mathbb{W}\left(\left\{c_R^T\left(\{w_{R,i}\}\right)\right\}\right),$$

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 implies

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

3.3 Limited Factor Price Equalisation

Since workers are imperfectly substitutable, they induce spillovers within firms, and consequently are not paid their marginal product.[20] Mirroring this, the equation 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) shows the industry wage bill *per capita* is equalized, formally

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

[19] In equilibrium, the type share is

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

[20] 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.

Second, summing across types in (3.5) implies

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

so average wages are constant across regions. This is summarized as

Proposition 3 *Average wages are equalized across regions.*

Proposition 3 shows that while our model allows for heterogeneity of wages by worker type, general equilibrium forces still imply that factor price equalization holds *on average*.

3.4 Regional Specialisation 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, $\mathbb{M}_R^T \cdot G\left(\overline{\eta}_R^T\right)/\mathbb{P}_R$. 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 (3.6):

$$\text{Firms per Capita, R to R}': \quad \frac{\mathbb{M}_R^T \cdot G\left(\overline{\eta}_R^T\right)/\mathbb{P}_R}{\mathbb{M}_{R'}^T \cdot G\left(\overline{\eta}_{R'}^T\right)/\mathbb{P}_{R'}} = \frac{u_{R'}^T}{u_R^T} = \left(\frac{c_{R'}^T}{c_R^T}\right)^{\alpha_L^T} \tag{3.6}$$

Equation (3.6) 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 4 *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 an estimator for the structural model parameters above. The estimator involves two regressions, with a simple intervening computation. The first stage equation determines firm labor demand, and unlike many approaches, is based on the firm-level shares of workers hired across regions. The second stage equation uses regional unit labor costs from the first stage to estimate the production function. Feasibility is illustrated by simulating a data set consistent with the model above and recovering model primitives accurately with the estimator.

4.1 First Stage Estimation

Equation (2.9) determines the share of each type of workers hired in each region R and industry T. Taking logs and allowing for errors ϵ_{ij} across firms and types implies

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

To estimate this equation we use a combination of type and region dummies.[21] To further explain how regional variation identifies the model we discuss equilibrium hiring predicted by Equation (4.1) in Appendix D.2.

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

$$\underline{m}_{ij}^{T} \equiv \underline{m}_{i}^{T} \cdot \exp\left(\text{Controls}_j \gamma_i^T\right), \tag{4.2}$$

where γ_i^T is a type-industry specific estimate which influences 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_{Rj}^{T}. We now discuss how the first stage estimates are used to estimate the production function in a second stage.

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

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

[21] 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 $\left(\theta^T / \beta^T\right) k \ln \underline{m}_i^T / \underline{m}_{\mathbb{S}}^T$.

Rearranging yields the estimating equation

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

The entire estimation procedure is now briefly recapped.[22]

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 by firm j, estimate Equation (4.1) for each industry, using type and region dummies.
2. Recover $\widehat{\theta^T}$, $\widehat{k}$, $\widehat{\underline{m}_i^T/\underline{m}_{\mathbb{S}}^T}$ and $\widehat{\gamma_i^T}$. Bootstrap standard errors or use the delta method.
3. Calculate $\widehat{\Delta \ln c_{Rj}^T}$ from Equation (2.7) using regional data and estimates from Step 2.
4. Estimate Equation (4.5) using $\widehat{\Delta \ln c_{Rj}^T}$.

Having laid out both a model detailing the interaction of firm technologies with local market conditions and specifying an estimation strategy, we now apply the method to China. The next section discusses these data in detail while the sequel presents our results.

5 Data

Firm data come from the 2004 Survey of Industrial Firms conducted by the Chinese National Bureau of Statistics, which includes all state owned enterprises and private enterprises with sales over 5 million RMB. The data include firm ownership, location, industry, employees by education level, profit and cash flow statements. Firm capital stock is reported fixed capital, less reported depreciation while materials are measured by value. For summary statistics, see Appendix E.3. From the Survey, a sample 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.

Regional wage distributions are calculated from the 0.5% sample of the 2005 China Population Census. The census contains the 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

[22] This specification is structural, but treats some model parameters as ancillary. In the Appendix, we illustrate the estimator by simulating firms which obey the production model specified above and apply these steps. In the simulation, the two stage estimator explains 97% of the variation in firm output, suggesting that the time savings of this estimator likely outweigh any gain from a completely specified estimator.

is recovered from the average annual income of employees by education using census data.[23]

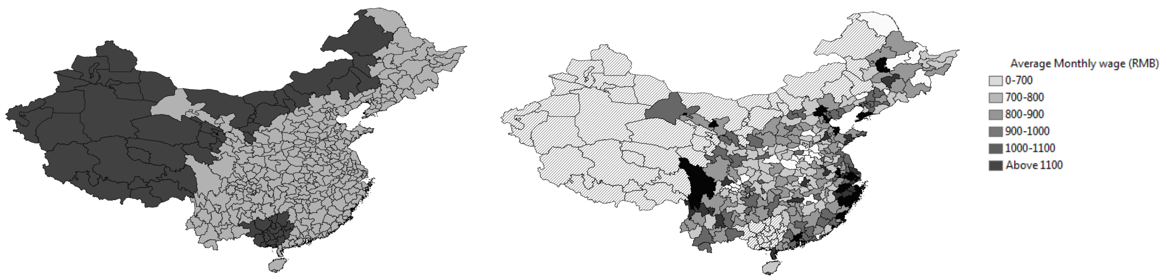
In addition, GIS data from the China Data Center at the University of Michigan locates firms at the county and prefecture level. Port data is provided by GIS data and supplemented by inland port data from the World Port Index. These data provide controls for urban status, distance to port and Economic Zone status.

Figure 5.1a illustrates the prefectures of China, which we define as regions from the perspective of the model above. Prefectures illustrated by a darker shade in the Figure operate under substantially different government policies and objectives. These regions typically have large minority populations or historically distinct conditions, with the majority declared as autonomous regions, and have idiosyncratic regulations, development, and educational policies.[24] We restrict attention to the lighter shaded regions of Figure 5.1a, preserving 284 prefectures displaying distinct labor market conditions.[25]

Figure 5.1: Chinese Prefectures

(a) Sample

(b) Average Monthly Income of Employees (2005)



5.1 Regional Variation

Key to our analysis is regional variation in skill distribution and wages. Here we briefly discuss both, with further details in Appendix E. Monthly incomes vary substantially across China as illustrated in Figure 5.1b. This is due to both the composition of skills (proxied by education) across regions and the rates paid to these skills. Figure 5.2 contrasts educational distributions of the labor force. Figure 5.2(a) shows those with a Junior High School education (the mandated level in China), while Figure 5.2(b) displays those with a Junior College or

[23]While firm data is from 2004 and census data is from 2005, firm skill mix is remarkably stable over time: Ilmakunnas and Ilmakunnas (2011) find the standard deviation of plant-level education years is very stable from 1995-2004 in Finland, and Parrotta et al. (2011) find that a firm-level education diversity index was roughly constant over a decade in Denmark.

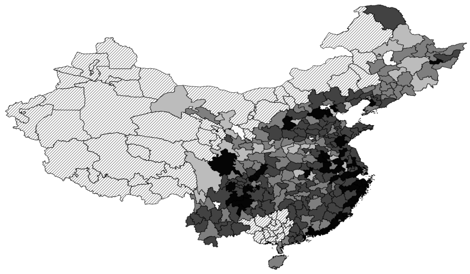
[24]See the Information Office of the State Council of the People's Republic of China

[25]In 2005, China was composed of thirty three Provinces and we exclude the five Autonomous Provinces and one predominantly minority Non-Autonomous Province.

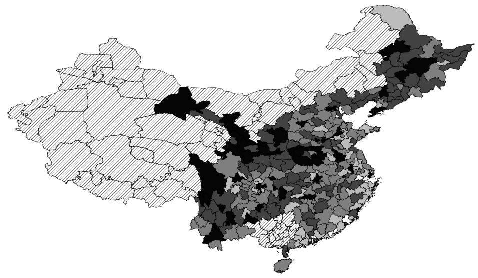
higher level of attainment.

Figure 5.2: Low and High Educational Attainment Across China (2005)

(a) % labor Force with ≤ Junior High School



(b) % labor Force with ≥ Junior College



The differing composition of input markets across China in 2004-2005 stem from many factors, including the dynamic nature of China's rapidly growing economy, targeted economic policies and geographic agglomeration of industries across China.[26] Faber (2012) finds that expansion of China's National Trunk Highway System displaced economic activity from counties peripheral to the System. Similarly, Baum-Snow et al. (2012) show that mass 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 Chinese economic policies is provided by Defever and 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 quantitative 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.[27] Given that rural to urban migration typifies the pattern of structural transformation underway, 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 et al., 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.

[26]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.

[27]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 et al. (2012).

5.2 Worker Types

Our definition of workers is people between ages 15 and 65 who work outside the agricultural sector and are not employers, self-employed, or in a family business. 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.[28] 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.

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 A.3 and A.4 of Appendix C. A representative set of estimates for the General Machines 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.

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

[28] Differentiation of gender for low skill labor is especially important in developing countries as a variety of influences result in imperfect substitutability across gender. Bernhofen and Brown (2011) distinguish between skilled male labor, unskilled male labor and female labor and find that the factor prices across these types differ substantially.

capital, do not appreciably alter the results. Other controls which did not appreciably alter the results include State Ownership and the percentage of migrants.

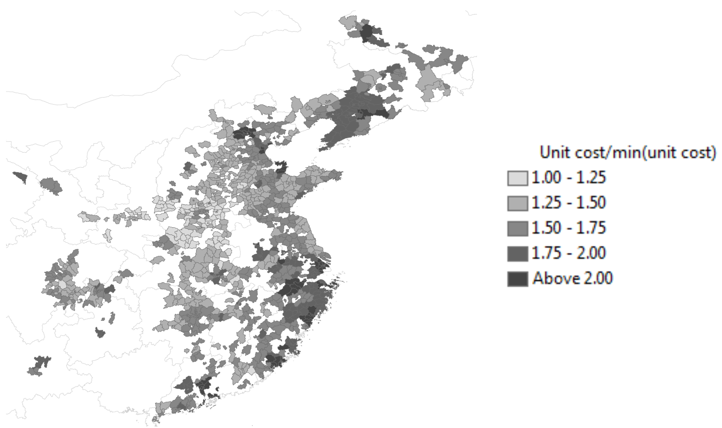
Table 1: First Stage Results: General Machines

Primary Variables	ln (% Hired)	Firm Controls	
$\ln(w_{R,i})$	-2.687***	$\underline{m}_1$ ∗ Urban Dummy	-1.384***
$\ln(a_{R,i})$	1.794***	$\underline{m}_2$ ∗ Urban Dummy	-0.980***
$\underline{m}_1$ (≤Junior HS: Female)	-10.170***	$\underline{m}_3$ ∗ Urban Dummy	0.427***
$\underline{m}_2$ (≤Junior HS: Male)	-6.171***	$\underline{m}_4$ ∗ Urban Dummy	2.336***
$\underline{m}_3$ (Senior High School)	-3.180***	$\underline{m}_1$∗% Foreign Equity	-2.448***
		$\underline{m}_2$∗% Foreign Equity	-1.864***
		$\underline{m}_3$∗% Foreign Equity	0.311***
Regional Controls		$\underline{m}_4$∗% Foreign Equity	3.847***
$\underline{m}_1$∗% Non-Ag Hukou	-5.957***	$\underline{m}_1$ ∗ ln (Firm Age)	0.934***
$\underline{m}_2$∗% Non-Ag Hukou	-3.072***	$\underline{m}_2$ ∗ ln (Firm Age)	0.403***
$\underline{m}_3$∗% Non-Ag Hukou	-3.218***	$\underline{m}_3$ ∗ ln (Firm Age)	0.143***
$\underline{m}_4$∗% Non-Ag Hukou	-7.026***	$\underline{m}_4$ ∗ ln (Firm Age)	0.351***
Observations: 62,908. R^2 : 0.139		Includes Regional Fixed Effects	

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

These first stage estimates are interesting in themselves, as the model then implies the unit cost function for labor by region. The dispersion of estimated unit labor costs in the General Purpose Machine industry are depicted in Figure 6.1.

Figure 6.1: Geographic Dispersion of unit labor Costs: General Machines



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, where the regional unit labor costs are calculated using regional data and the first stage estimates.

Table 2: Model Primitive Estimates

Industry	k	θ	Industry	k	θ
Beverage	2.12 black(.38)	1.24 (.08)	Paper	6.25 (3.8)	0.73 (.11)
Electrical	2.60 black(.15)	1.22 (.02)	Plastic	3.51 (.29)	1.08 (.03)
Food	1.59black (.36)	1.28 (.13)	Printing	3.93 (.60)	1.04 (.04)
General Machines	2.50 black(.14)	1.22 (.03)	PC & AV	2.21 (.14)	1.41 (.04)
Iron & Steel	3.21 black(.56)	1.00 (.06)	Rubber	1.63 (.61)	1.15 (.19)
Leather & Fur	2.15 black(.70)	0.76 (.14)	Specific Machines	1.63 (.18)	1.43 (.07)
Precision Tools	2.34 black(.18)	1.43 (.05)	Textile	3.73 (.36)	0.95 (.03)
Metal Products	3.20 black(.24)	1.10 (.03)	Transport	1.26 (.24)	1.38 (.13)
Non-ferrous Metal	2.89 black(.38)	1.15 (.05)	Wood	1.52 (.22)	1.62 (.17)
Non-metal Products	2.02 black(.16)	1.25 (.04)	Standard Errors reported in parentheses.		

Table 3: Second Stage Estimates

Industry	α_L	α_K	α_M	Industry	α_L	α_K	α_M
Beverage	.13 (.05)	.10 (.01)	.70 (.04)	Paper	.18 (.36)	.14 (.03)	.53 (.28)
Electrical	.25 (.01)	.14 (.01)	.47 (.01)	Plastic	.27 (.04)	.14 (.01)	.41 (.02)
Food	.14 (.08)	.09 (.01)	.70 (.06)	Printing	.09 (.06)	.22 (.01)	.55 (.03)
General Machines	.17 (.02)	.12 (.01)	.60 (.01)	PC & AV	.16 (.01)	.21 (.01)	.43 (.01)
Iron & Steel	.40 (.06)	.07 (.01)	.48 (.05)	Rubber	.06 (.15)	.13 (.02)	.63 (.10)
Leather & Fur	.10 (.11)	.13 (.02)	.59 (.07)	Specific Machines	.10 (.03)	.16 (.01)	.55 (.02)
Precision Tools	.20 (.01)	.16 (.01)	.43 (.01)	Textile	.12 (.05)	.11 (.01)	.61 (.03)
Metal Products	.24 (.01)	.14 (.01)	.46 (.01)	Transport	.04 (.03)	.15 (.01)	.65 (.02)
Non-ferrous Metal	.40 (.03)	.08 (.01)	.43 (.02)	Wood	.22 (.11)	.10 (.02)	.56 (.08)
Non-metal Products	.20 (.02)	.07 (.01)	.61 (.02)	Standard Errors reported in parentheses.			

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.[29] 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.

[29] 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.

6.2 Implied Productivity Differences Across Firms

Table 4 quantifies the implied differences in unit labor costs and productivity across regions. The c_R^T column 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 contains the differences in productivity implied by unit labor costs as laid out in Section 2.4, taking into account substitution into non-labor inputs. For example, consider two firms in General Machines 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 firm is 1.41 times greater than the higher cost firm. From Table 3 above, the estimated share of wages in production is $\alpha_L^T = .17$, so the lower cost firm will produce $1.41^{.17} = 1.06$ 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
Beverage	1.51	1.06	Paper	1.66	1.07
Electrical	1.38	1.08	Plastic	1.35	1.09
Food	1.81	1.09	Printing	1.37	1.03
General Machines	1.41	1.06	PC & AV	1.44	1.06
Iron & Steel	1.34	1.13	Rubber	2.16	1.04
Leather & Fur	1.92	1.04	Specific Machines	1.99	1.08
Precision Tools	1.80	1.13	Textile	1.37	1.04
Metal Products	1.33	1.07	Transport	4.01	1.04
Non-ferrous Metal	1.45	1.17	Wood	1.47	1.10
Non-metal 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 local 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%.[30]

Table 5 examines the variance of productivity across industries under our unit cost method and under an approach estimating output by a Cobb-Douglas combination of capital, materials and the number of each worker type. Table 5 also shows the average percentage that unexplained productivity is reduced per firm under the unit labor cost method.

Since firms locate freely, the model predicts that these substantial cost differences drive

[30]Most models used in production estimation assume perfect labor substitutability. Such models imply that, conditional on wages, the local composition of the workforce is irrelevant for hirin. Our approach is sensitive to local factor supply and an empirical comparison with other models is presented in Appendix C.2.

economic activity towards more advantageous locations, which we now examine.

Table 5: Percentage of Productivity Explained by Unit Cost Method

Industry	Unit Cost σ^2	Four Types σ^2	Avg % Reduced	Industry	Unit Cost σ^2	Four Types σ^2	Avg % Reduced
Beverage	0.41	0.54	0.18	Paper	0.36	0.65	0.30
Electrical	0.40	0.67	0.27	Plastic	0.22	0.64	0.43
Food	0.37	0.61	0.28	Printing	0.49	0.56	0.10
General Machines	0.44	0.59	0.16	PC & AV	0.73	0.94	0.21
Iron & Steel	0.32	0.46	0.19	Rubber	0.55	0.56	0.08
Leather & Fur	0.23	0.66	0.43	Specific Machines	0.51	0.61	0.10
Precision Tools	0.45	0.46	0.07	Textile	0.39	0.45	0.11
Metal Products	0.48	0.69	0.22	Transport	0.58	0.59	0.04
Non-ferrous Metal	0.27	0.43	0.24	Wood	0.26	0.45	0.27
Non-metal products	0.44	0.56	0.15				

6.3 Firm Location

Per capita volumes of economic activity across regions are determined by Equation (3.6), which states that relatively lower industry labor costs should attract relatively more firms to a region. Table 6 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.[31] While the point estimates vary, the median significant estimates is about -.8, indicating a 10% increase in unit labor costs is associated with an 8% decrease in value added per capita.

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 an estimator 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 first stage to introduce local labor

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

Table 6: 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
Beverage	-0.696^b	(.274)	-0.122	(.200)	18.96^a	(3.36)	155	.03
Electrical	-0.057	(.403)	-1.567^a	(.259)	11.98^b	(4.80)	166	.22
Food	-0.553^b	(.229)	-0.397^b	(.179)	15.49^a	(2.15)	171	.04
General Machines	-0.705^c	(.400)	-1.314^a	(.340)	19.68^a	(4.86)	195	.11
Iron & 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
Precision Tools	-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-metal 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
PC & AV	-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 Machines	-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	-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.

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. Our estimates imply an interquartile difference in labor costs of 30 to 80 and productivity differences of 3 to 17 percent. The results suggest that team technologies combined with favorable factor market conditions explain substantial differences in firm input use and productivity. This shows that modelling a firm's local environment yields substantial insights into production patterns that 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. Taken as a whole, our results show that policy changes which influence the composition of regional labor markets 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 analysing 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 is also suitable for analysing firm behavior across national borders. Further work could leverage or extend the approach of combining firm, census and geographic data to better understand the role of local factor markets on firm behavior.

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Appendix

The organization of the Appendix is as follows: Section A contains proofs of results discussed in the main text. Section B evaluates the efficacy of the reduced form model estimator. Section C contains more detail regarding model estimates. Three supplemental appendices are provided for online publication: Section D contains additional details on the model solution and properties. Section E contains summary statistics. Section F contains supplemental empirical results.

A Further Model Discussion and Proofs

A.1 Optimality of Hiring All Worker Types

If $\beta^T > 0$ then it is optimal for a firm to hire all types of workers. Let c_R^T denote a firm's unit labor cost when all worker types are hired, and $\check{c}_R^T$ the unit labor cost if a subset of types $\mathbb{T} \subset \{1, \ldots \mathbb{S}\}$ is hired. For the result, we require that $c_R^T \leq \check{c}_R^T$ for all $\mathbb{T}$. Considering a firm's cost minimization problem when $\mathbb{T}$ are the only types available shows with Equation (2.7) that

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

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 $\beta^T/\theta^T\left(1-k\right) \leq 0$, which holds for $\beta^T > 0$ since $k > 1$.

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 (3.5) holds. Since all prices are nominal, WLOG we normalize $I_{\text{Agg}} = 1$ in the following. There is a wage function that uniquely solves (3.5) given unit labor costs. 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 $h_{R,i}\left(x\right) \equiv \sum_t \alpha_L^t \sigma^t \left(c_R^t\right)^{k/\beta^t-1} \left(x^{1-k} a_{R,i}\left(\underline{m}_i^t\right)^k / f\left(k-1\right)\right)^{\theta^t/\beta^t}$, $g_{R,i}\left(x\right) \equiv a_{R,i}x$. For the result we require a unique x s.t. $g_{R,i}\left(x\right) = h_{R,i}\left(x\right)$. $g_{R,i}$ is strictly increasing and ranges from 0 to ∞, while $h_{R,i}\left(x\right)$ is strictly decreasing, and ranges from ∞ to 0, so x exists and is unique. 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 (2.7), 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 (3.5). We first show that any equilibrium wage vector must lie in a strictly positive, compact set $\times_{R,i}\left[\underline{w}_{R,i}, \overline{w}_{R,i}\right]$. From (3.5), $H_{R,i}^{\theta^T}/\Sigma_j H_{R,j}^{\theta^T} \in [0,1]$ so $w_{R,i} \leq \overline{w}_{R,i} \equiv \sum_t \alpha_L^t \sigma^t / a_{R,i}$. Let

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

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

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

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 $\mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)$. Since necessarily $\mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right) = \{\hat{w}_R\}$, $\mathbb{W}$ is increasing in $\left\{c_R^T\right\}$, and $c_R^T\left(w_R\right)$ is increasing in w_R, we have $\{\hat{w}_R\} = \mathbb{W}\left(\left\{c_R^T\left(\hat{w}_R\right)\right\}\right) \geq \mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right) \geq \{\underline{w}_R\}$. 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 $\left\{c_R^T\right\}$, $\times_R\left[\underline{c}_R^T, \bar{c}_R^T\right]$, by

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

Now consider the mapping $\mathbb{C}\left(\left\{c_R^T\right\}\right) \equiv \left\{c_R^T \circ \mathbb{W}\left(\left\{c_R^T\right\}\right)\right\}$ on $\times_R\left[\underline{c}_R^T, \bar{c}_R^T\right]$, which is continuous on this domain. By above, $\mathbb{W}_{R,i}\left(\left\{c_R^T\right\}\right) \leq \overline{w}_{R,i}$ for each R, i so $\mathbb{C}\left(\left\{c_R^T\right\}\right) \leq \left\{\bar{c}_R^T\right\}$. Also by above, $\mathbb{C}\left(\left\{c_R^T\right\}\right) \geq \left\{c_R^T \circ \mathbb{W}\left(\left\{c_R^T\left(\underline{w}_R\right)\right\}\right)\right\} \geq \left\{c_R^T\left(\left\{\underline{w}_R\right\}\right)\right\} = \left\{\underline{c}_R^T\right\}$. Thus $\mathbb{C}$ maps $\times_R\left[\underline{c}_R^T, \bar{c}_R^T\right]$ into itself and by Brouwer's fixed point theorem, there exists a fixed point $\left\{\widehat{c}_R^T\right\}$, which implies $\mathbb{W}\left(\left\{\widehat{c}_R^T\right\}\right)$ is an equilibrium wage vector.

B Model Simulation and Estimator Viability

A model simulation was constructed using parameters given in Table A.1. In the simulation, firms maximize profits conditional on local market conditions, and applying the estimator above produces Tables A.2 and A.2. The Estimate column contains results while the model values are reported in the Predicted column. The estimates are very close to the predicted values. Figure A.1 further confirms this by plotting the simulated and predicted differences in the share of workers hired. For ease of comparison, Figure A.1 plots regional frequencies along the horizontal axis and (linearly) normalized wages for each worker type. As the Figure suggests, the R^2 in both cases are high: .99 for the first stage and .97 for the second stage.

Figure A.1: Simulation Fit

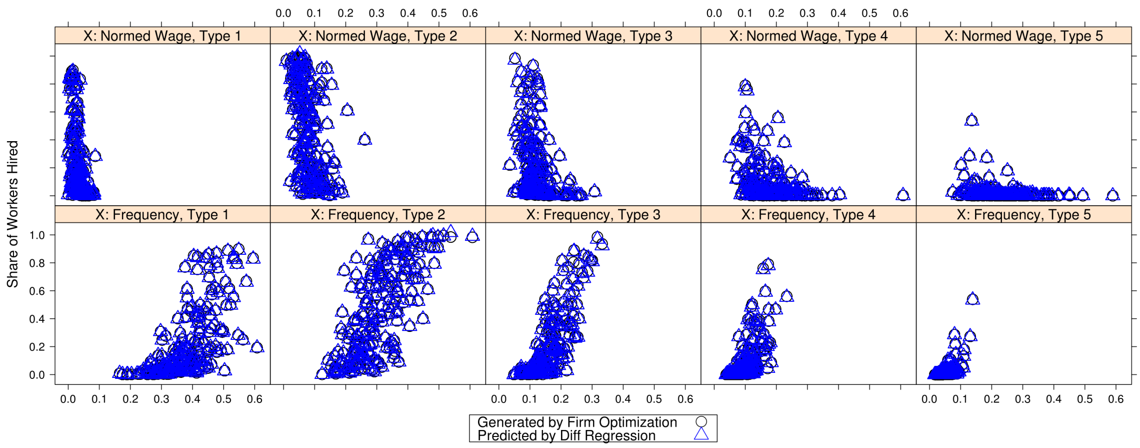


Table A.1: Simulation details

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.	∼LogNormal $\mu = (12, 24, 36, 48, 60)$, $\sigma = 13$.
$\{a_{R,i}\}$	Regional type frequencies.	∼LogNormal $\mu = (.4, .3, .15, .1, .05)$, $\sigma = 13$, scaled so that frequencies sum to one.
K, M	Firm capital and materials.	∼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.	∼LogNormal $\mu = 0$, $\sigma = 1$.
Coeff	Exponent on Control.	Control Coeff$= \pi$.
$\{\omega_j\}$	Firm idiosyncratic wage costs.	∼LogNormal $\mu = 0$, $\sigma = .1$.

Sample: 200 regions with 20 firms per region, with errors ∼LogNormal($\mu = 0$, $\sigma = 12$).

Table A.2: Simulation Results

[Simulation First Stage Estimates: Technology and Human Capital]

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

[Simulation Second Stage Estimates: Production Parameters]

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

C Model Estimates

Table A.3: First Stage Estimates I

Industry	Beverage	Electrical Equip	Food	General Machines	Iron & Steel	Leather & Fur	Precision Equipment	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 (≤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 (≤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 A.4: First Stage Estimates II

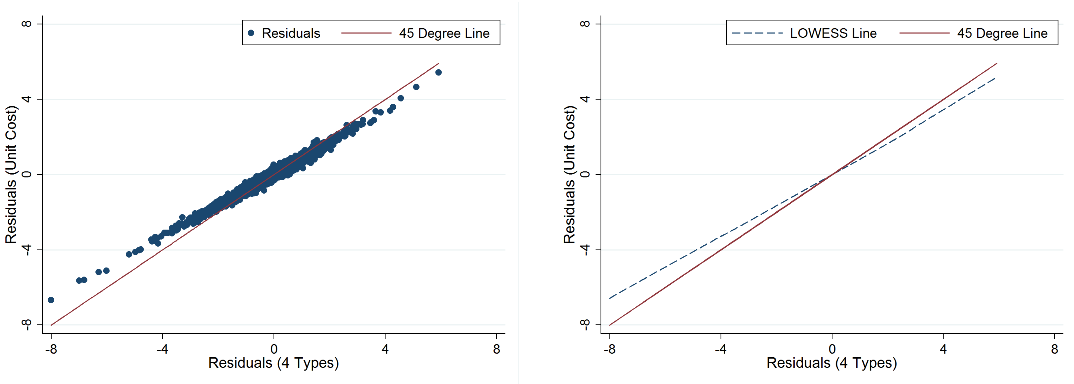
Industry	Other Non-metal	Paper	Plastic	Printing	PC & AV Equipment	Rubber	Specific Machines	Textile	Transport Equip	Wood
	Dependent Variable: $\ln(\%\text{type})$									
$\ln(w_{R,i})$	-1.693^{a}	-1.542^{a}	-3.324^{a}	-3.491^{a}	-3.371^{a}	-0.854	-1.260^{a}	-2.230^{a}	-0.372	-1.220^{b}
$\ln(a_{R,i})$	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
$m_1 * \ln$(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
$m_2 * \ln$(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
$m_3 * \ln$(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
$m_4 * \ln$(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.

C.1 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 A.1 contrasts unexplained productivity (estimation residuals) when unit labor costs are used with estimates that measure labor by including the employment of each worker type. 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 A.1: Productivity: unit labor Costs vs Total Employment (General Machines)



C.2 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 mean of the second stage estimates using these labor measures are contrasted with our method in Table A.5 (full results in Table A.13 of the Supplemental Appendix). 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.[32] Most notably, the capital share tends to be higher under our approach, while the labor share is substantially lower.

Pushing this comparison further, Table A.12 predicts the propensity to export of firms by residual firm productivity. The first column shows the results under our unit cost method. The

[32]The residuals remaining after the second estimation step, which are often interpreted as idiosyncratic firm productivity, are compared in Appendix C.1.

Table A.5: Second Stage Estimates vs Homogeneous labor Estimates

	unit labor Cost			Total Wage Bill			Total Employment		
	α_L	α_K	α_M	α_L	α_K	α_M	α_L	α_K	α_M
Average	0.18	0.13	0.55	0.29	0.09	0.54	0.28	0.09	0.58

second and third columns show the results when labor is measured as perfectly substitutable (either by employment of each type 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 exports as the other measures. Section F.2 of the Appendix shows that similar results hold when examining sales growth and three year survival rate: productivity under the unit cost approach is more important in predicting firm performance, suggesting the other measures conflate the role of advantageous factor markets with productivity.

Table A.6: Explaining Propensity to Export with Productivity

	Export Dummy (2005)		
Productivity under Unit Cost method	0.0242***		
	(0.00393)		
Productivity under L = 4 Types		0.0131***	
		(0.00241)	
Productivity under L = Wage Bill			0.0168***
			(0.00252)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.202	0.201	0.202

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

D Supplemental Derivations

D.1 Derivation of Region-Techonology Budget Shares

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, $\widetilde{\eta}_R^T$:

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

Using the profit maximizing price P_{Rj}^{T} and combining Equations (2.11), (3.2) and (3.1) then yields the equilibrium quantity produced,

$$Q_{Rj}^{T} = \rho I_{\text{Agg}} \left(u_{R}^{T} \eta_j \left(U_{R}^{T} / \sigma_{R}^{T} \right)^{1/\rho} \right)^{\rho/(\rho-1)} / u_{R}^{T} \eta_j \sum_{t,r} \left(\sigma_{r}^{t} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{r}^{t} \widetilde{\eta}_{r}^{t}. \tag{D.1}$$

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

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

Consequently, since free entry implies expected profits must equal expected fixed costs, the mass of entrants $\mathbb{M}_{R}^{T}$ solves the implicit form[33]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\left(\sigma_{R}^{T} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{R}^{T} \widetilde{\eta}_{R}^{T} / \sum_{t,r} \left(\sigma_{r}^{t} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{r}^{t} \widetilde{\eta}_{r}^{t} \right) = \mathbb{M}_{R}^{T} u_{R}^{T} \left(f_e G \left(\overline{\eta}_{R}^{T} \right) + F_e \right), \tag{D.3}$$

while the equilibrium cost cutoffs $\overline{\eta}_{R}^{T}$ solve the zero profit condition[34]

$$\frac{1-\rho}{\rho} I_{\text{Agg}} \left(\sigma_{R}^{T} \right)^{1/(1-\rho)} \left(u_{R}^{T} \overline{\eta}_{R}^{T} \left(U_{R}^{T} \right)^{1/\rho} \right)^{\rho/(\rho-1)} = u_{R}^{T} f_e \sum_{t,r} \left(\sigma_{r}^{t} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{r}^{t} \widetilde{\eta}_{r}^{t}. \tag{D.4}$$

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

$$\int_{0}^{\overline{\eta}_{R}^{T}} \left(\eta_{z}^{T} / \overline{\eta}_{R}^{T} \right)^{\rho/(\rho-1)} dG(z) / G\left(\overline{\eta}_{R}^{T} \right) = 1 + F_e / f_e G\left(\overline{\eta}_{R}^{T} \right).$$

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

$$U_{R}^{T} u_{R}^{T} / \sigma_{R}^{T} = \left[(1-\rho) I_{\text{Agg}} / \rho f_e \sum_{t,r} \left(\sigma_{r}^{t} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{r}^{t} \widetilde{\eta}_{r}^{t} \right]^{1-\rho} / \left(\overline{\eta}_{R}^{T} \right)^{\rho}. \tag{D.5}$$

where the RHS does not vary by region or technology. Combining this equation with (3.1) 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

[33] To see a solution exists, note that for fixed prices, $\{\widetilde{\eta}_{R}^{T}\}$, and $\{\overline{\eta}_{R}^{T}\}$, 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 $H\left(\left\{ \widetilde{\mathbb{M}}_{R}^{T} \right\} \right) \equiv (1-\rho) I_{\text{Agg}} \left(\left(\sigma_{R}^{T} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{R}^{T} \widetilde{\eta}_{R}^{T} / \sum_{t,r} \left(\sigma_{r}^{t} \right)^{1/(1-\rho)} \widetilde{\mathbb{M}}_{r}^{t} \widetilde{\eta}_{r}^{t} \right) / \rho u_{R}^{T} \left(f_e G \left(\overline{\eta}_{R}^{T} \right) + F_e \right)$.

[34] 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.

time, using Equation (D.5) reduces (D.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.

D.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:

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

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

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

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 $\chi_{i,R,T}$:

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

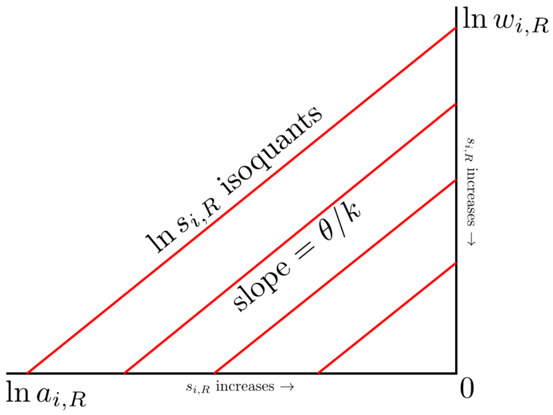
Investigation shows that each $\chi_{i,R,T}$ is between zero and one. Combining Equations (D.6-D.8) and Equations (D.9-D.11) shows that the direct effect dominates since

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

$$d \ln s_{R,T,i} / d \ln \underline{m}_i^T = \left[k\theta^T / \beta^T \right] \chi_{i,R,T} > 0. \tag{D.14}$$

Equations (D.12-D.14) summarize the relationship between regions and labor market characteristics. 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 A.1.

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



D.3 Regional Variation in Theory: Isoquants

Equations (D.12-D.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

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

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 (D.15) shows that firms would keep the same share of type i workers if the availability Δ_a increases concurrently so that Equation (D.15) holds.

D.4 Derivation of unit labor Costs

unit labor costs by definition solve

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

Under the parameterization $\Psi\left(h\right) = 1 - h^{-k}$, Equations (2.1) become

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

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

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

Substitution now yields

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

Further reduction and the definition of β^T shows that

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

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

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

From the definition of the cost function we have

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

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

$$1 = \sum_i \left(k-1\right)/k \cdot H_i^{\theta^T} + N f = \left(k-1\right)/k + N f,$$

and therefore $N = 1/fk$. Now from Equation (D.20) c_R^T is seen to be Equation (2.7).

D.5 Derivation of Employment Shares

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

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

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 (D.21),

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

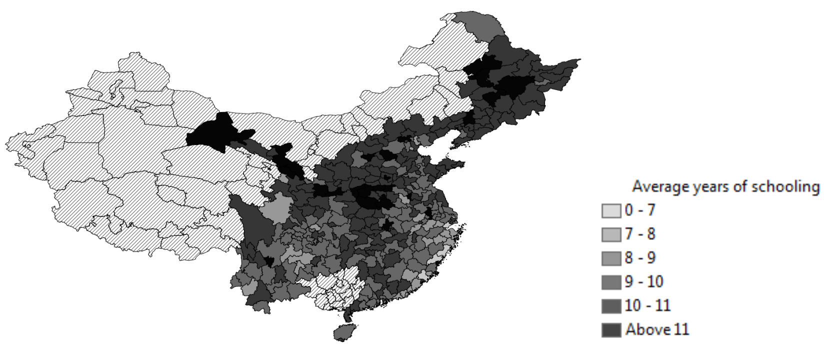
labor is also consumed by the fixed search costs which consist of $N|_{L=1} \cdot f = 1/k$ labor units. Therefore, if $\widetilde{A}_{R,i}^T$ denotes the total number of type i workers hired to make $L = 1$, necessarily $\widetilde{A}_{R,i}^T = A_{R,i}^T + \widetilde{A}_{R,i}^T/k$ so $\widetilde{A}_{R,i}^T = k\left(k-1\right)^{-1} A_{R,i}^T$, 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 $\sum_i L_R^T \widetilde{A}_{R,i}^T = L_R^T \left(c_R^T\right)^{k/\beta^T} \left(\tilde{c}_R^T\right)^{-k\theta^T/\beta^T}$, where $\tilde{c}_R^T$ denotes the unit labor cost function at wages $\left\{w_{R,i}^{k/(k-1)\theta^T}\right\}$[35].

E Supplemental Summary Statistics

E.1 Educational Summary Statistics

UNICEF suggests that the typical Chinese primary school entrance age is 7 (Source: childinfo.org). Compulsory education lasts nine years (primary and secondary school) and ends around age sixteen. Figure A.1 illustrates the average years of schooling for the Chinese labor force, while Table A.7 displays the frequency of each worker type and their average monthly wages by Province.

Figure A.1: Chinese Educational Attainment (labor Force 2005)



[35]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 $L = 1$.

Table A.7: 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

E.2 Provincial Summary Statistics

Table A.8: Descriptive Statistics by Province (2005)

	Manufacturing		Population Census			
Province	Firm Count	Avg Workers	# of Regions	# Region-Industries	Monthly Wage	Avg Yrs 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

E.3 Industrial Summary Statistics

Table A.9 presents the distribution of firms by industry and other descriptive statistics.

F Supplemental Empirical Results

F.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

Table A.9: Manufacturing Survey Descriptive Statistics (2005)

				Share of				
	# of	# of	Avg # of		White		State	Foreign
Industry	firms	Regions	workers	Female	Collar	Export	Equity	Equity
Beverage	2,225	155	219.20	0.281	0.114	0.150	0.107	0.121
Electrical	12,241	166	201.58	0.289	0.106	0.351	0.030	0.195
Food	3,807	171	193.98	0.321	0.091	0.266	0.060	0.202
General Machines	15,727	195	152.68	0.205	0.117	0.262	0.047	0.115
Iron & 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
Precision Tools	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-metal 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
PC & AV	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 Machines	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	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

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 A.10 of Appendix F.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.

F.2 Firm Performance Characteristics and Productivity

F.3 Production Estimates by Method

Table A.13 compares the production coefficients under three measures of labor: unit labor costs, total wages, and employment of each worker type. In the latter case, the coefficient for type i workers are labeled α_L^i.

Table A.10: 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
Beverage	1.052***	(0.0147)	-0.904***	(0.204)	2223	0.85
Electrical	1.018***	(0.0103)	-0.370***	(0.138)	12213	0.86
Food	1.032***	(0.0104)	-0.602***	(0.144)	3766	0.83
General Machines	1.020***	(0.0063)	-0.365***	(0.091)	15711	0.84
Iron & 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
Precision Tools	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-metal 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
PC & AV	1.021***	(0.0172)	-0.354	(0.224)	6685	0.86
Rubber	1.000***	(0.0132)	-0.133	(0.182)	2195	0.87
Specific Machines	1.036***	(0.0105)	-0.580***	(0.139)	7780	0.83
Textile	0.981***	(0.0060)	0.132	(0.084)	18281	0.86
Transport	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.

Table A.11: Explaining Growth with Productivity

	Sales Growth Rate (2005-7)		
Productivity under Unit Cost method	-0.0839**		
	(0.0372)		
Productivity under L = 4 Types		-0.0619***	
		(0.0239)	
Productivity under L = Wage Bill			-0.0607**
			(0.0258)
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 A.12: Explaining Survival with Productivity

	Survival Rate (2005-7)		
Productivity under Unit Cost method	0.0188***		
	(0.00230)		
Productivity under L = 4 Types		0.0115***	
		(0.00157)	
Productivity under L = Wage Bill			0.0103***
			(0.00157)
Prefecture and Industry FE	Yes	Yes	Yes
Observations	141,409	141,409	141,409
R-squared	0.023	0.023	0.022

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

Table A.13: Second Stage Estimates vs Homogeneous Labor Estimates

	Unit Labor Cost			Total Wage Bill			Employment of Each Type					
Industry	α_L	α_K	α_M	α_L	α_K	α_M	α_L^1	α_L^2	α_L^3	α_L^4	α_K	α_M
Beverage	.13	.10	.70	.23	.06	.71	.07	.01	.07	.06	.07	.75
Electrical	.25	.14	.47	.34	.12	.47	.06	.02	.08	.12	.12	.53
Food	.14	.09	.70	.16	.06	.73	.07	.03	.09	.08	.12	.52
General Machines	.17	.12	.60	.25	.09	.61	.03	.01	.09	.03	.06	.76
Iron & Steel	.40	.07	.48	.25	.07	.68	.04	.03	.06	.08	.10	.66
Leather & Fur	.10	.13	.59	.27	.09	.55	.01	.07	.11	.05	.06	.71
Precision Tools	.20	.16	.43	.44	.08	.38	.02	.13	.07	.05	.09	.57
Metal Products	.24	.14	.46	.30	.12	.48	.09	.03	.05	.23	.11	.44
Non-ferrous Metal	.40	.08	.43	.17	.10	.65	.03	.04	.06	.02	.06	.71
Non-metal Products	.20	.07	.61	.20	.06	.67	.04	.04	.10	.07	.11	.55
Paper	.18	.14	.53	.28	.11	.52	.09	.02	.10	.08	.14	.47
Plastic	.27	.14	.41	.31	.13	.43	.04	.01	.08	.06	.09	.65
Printing	.09	.22	.55	.40	.14	.44	.07	.02	.10	.10	.17	.51
PC & AV	.16	.21	.43	.48	.14	.35	.11	.07	.08	.24	.16	.41
Rubber	.06	.13	.63	.31	.07	.55	.05	.07	.08	.11	.06	.56
Specific Machines	.10	.16	.55	.31	.10	.48	.03	.01	.06	.13	.11	.53
Textile	.12	.11	.61	.29	.07	.56	.03	.09	.08	.08	.06	.58
Transport	.04	.15	.65	.31	.09	.53	.03	.03	.06	.10	.09	.59
Wood	.22	.10	.56	.23	.08	.62	.03	.07	.07	.08	.07	.63
Average	.18	.13	.55	.29	.09	.54	.05	.03	.08	.09	.10	.59