How Sensitive Is Foreign Investment in China to Wage Differences? Skill Intensity, Product Market Competition, and Networks*

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December 24, 2009

* We thank Amil Petrin and Ken Train for providing guidance on the application of their methods. We have benefited by helpful suggestions and insights from Lee Branstetter, Judith Dean, Devashish Mitra, and seminar participants at the NBER China Working Group Meetings, the University of Nottingham, and the 2010 AEA meetings.

Abstract

Deeper international integration through an inflow of foreign direct investment alters domestic labor markets, whether by shifting the labor demand curve or by increasing the elasticity of demand for domestic workers. This paper uses the location choices of multinational firms investing in China as a window into the relationship between foreign investment and host-country labor demand. With data on 2884 manufacturing equity joint venture projects in China during 1993-1996, we investigate the extent to which an investor's sensitivity to wages depends on the skill intensity of the activity, product market competition, and source country development level. Using a control function technique for conditional logit developed by Petrin and Train (2005, 2006), we find a significant, elastic response of capital to wages; *ceteris paribus*, investors are attracted to locations with low wages. Moreover, investors involved in the least skill intensive activities exhibit the most wage sensitivity. The Broda-Weinstein (2006) U.S. import demand elasticity estimates for Chinese exports allow us to measure pass-through ability and we find that investors in those industries where China faces the most elastic import demand are the most sensitive to wages differences, even when we control for the skill-intensity of the manufacturing activity. We also find that while OECD investors are more responsive to wage differences overall, they are less likely to choose a location that has received a large share of prior foreign investment. Simulations of regional wage subsidies indicate that policies to shift investment to inland regions alter the composition as well as the location of investment.

I. Introduction

Foreign direct investment is desired as a source of new capital, for employment generation, to increase specialization and access world markets, and for technology transfer. As it offers these potential benefits, however, FDI also alters the host economy by integrating it more deeply into world markets. Deeper international integration influences domestic labor markets, whether by shifting the demand for workers differentiated by skill or by increasing the elasticity of demand for all domestic workers.[1] Where FDI is a significant source of new capital, the demand for local labor depends in part on the preference of foreign investors, about which surprisingly little is known. Understanding the response of foreign investors to increases in local labor costs, as may arise from enforcement of minimum wages or maximum work hours, is important because these responses shape the policy space available to local communities seeking better wages and working conditions.

This paper estimates the sensitivity of foreign investors to wage differences across Chinese provinces, accounting for factor intensity, output market conditions, and networks. As suggested by labor demand theory, we estimate how firms' wage sensitivity is conditioned by both the labor intensity of production and the price elasticity of demand for the good produced. While we know of no other location-choice study that considers the role played by final good demand, a simple model of profit maximization suggests that the extent to which firms can "pass-through" cost increases to consumers influences the weight placed by investors on wages relative to other location characteristics. Indeed, outsourcing decisions by multinational firms often refer to the necessity of cost savings due to fierce product market competition.

Applying a control function technique for conditional logit developed by Petrin and Train (2005, 2006) to data on 2884 manufacturing equity joint venture projects in China during 1993-

1996, we find a significant, elastic response of capital to wages; *ceteris paribus*, investors are attracted to locations with low wages. Moreover, investors involved in the least skill intensive activities exhibit the most wage sensitivity. We also estimate how product market competition conditions investor's sensitivity to wage differences, controlling for the skill intensity of the activity. We find that, *ceteris paribus*, investors in those industries where China faces the most elastic import demand are the most sensitive to wages differences. We also find significant differences between investors from the ethnically Chinese economies (ECE) of Hong Kong, Macau, and Taiwan and those from other, primarily OECD, source countries. ECE investors are less responsive to wage differences and more attracted to prior investment, a finding that may be consistent with these investors' ability to access informal personal networks in the context of weak formal institutions.[2] Simulations of regional wage subsidies indicate that policies to shift investment to inland regions alter the composition as well as the location of investment, suggesting that such policies increase the labor demand elasticity of subsidized areas.

Foreign investment is often courted by policymakers as a way to shift outward the demand for local labor. Because foreign investment also alters the composition of local production, however, its influence on local labor markets extends beyond a simple shift in labor demand. As emphasized by the Hicks-Marshall laws of derived demand, the own-wage elasticity of demand for labor is high when (a) the price elasticity of demand for the product being produced is high; and (b) when the cost of employing labor is a large share of total production costs.[3] These factors vary among sectors of the economy, implying that as the composition of production changes, so too does the aggregate labor demand elasticity.

China is a setting where these compositional changes from foreign investment are pronounced, both because of the size of the inflows and because investment is concentrated in particular sectors. After China reformed its foreign investment regime in 1992, the entry of foreign-invested enterprises (FIEs) fueled rapid export growth. During the following years of stable and liberal policy toward FDI, 1992-1996, these enterprises contributed 32% of fixed asset investment by all non-state firms and accounted for more than half of Chinese manufactured exports.[4] Lemoine (2000) estimates that FIEs accounted for about 11 percent of manufacturing employment during the 1990s, but shares varied widely by sector and province. As reported by Huang (2003), working with data from the 1995 Chinese Industrial Census, FIE sales as a share of all sales exceeded 50 percent in garments and footwear, leather, sporting goods, and electronics and communications. For coastal provinces that absorbed much of the foreign capital, FIE production was a particularly important source of employment growth.

To begin to understand how foreign investment affects the sensitivity of local employment to labor costs, we estimate the extent to which industry characteristics condition investors' demand for labor in particular locations. We use these estimates to simulate a wage-subsidy policy designed to move investment away from coastal locations toward less-developed inland locations. As noted above, a unique contribution of our analysis is an emphasis on product market competition. Positing a model with imperfect substitutability between Chinese made goods and other goods in the international market, we hypothesize that industries with relatively limited ability to pass-through cost increases to consumers will be more sensitive to wages when searching for offshore production locations. To measure pass-through ability in our empirical work, we use the Broda and Weinstein (2006) U.S. import demand elasticity estimates. These estimates are well suited for this purpose for several reasons. First, Broda and Weinstein estimate these elasticities using an econometric procedure derived from a model of consumer and firm behavior that we share and which fits the Chinese setting. Secondly, these estimates are based on literally thousands of observations and thus are quite precise. Lastly, the US market is the largest market for FIE exports from China and, thus, American market conditions reflect important constraints on the pricing behavior of firms exporting from China.

A second feature of our analysis is our use of the control function in conditional logit analysis, as pioneered by Petrin and Train (2006). The next section discusses the need to control for omitted variable bias in location choice studies and describes the control function approach. We follow with a model of location choice and the foundation for our estimation strategy. Section IV describes our unique sample of foreign investment projects and measures of industry characteristics. Section V presents the results of our econometric analysis, which are used in simulations presented in Section VI to gauge the implications of our results for policy.

II. Control Function Corrections for Omitted Attributes

Recent studies of the distribution of aggregate FDI flows among Chinese provinces or regions include Coughlin and Segev (2000), Wei, Liu, Parker and Vaidya (1999), Cheng and Kwan (2000), Fung, Iizaka, and Parker (2002), Gao (2002), and Fung, Iizaka, and Siu (2003). In all studies except one, the wage is found to be a statistically significant, negative determinant of the value of FDI flowing into a Chinese province or region. This result is robust to the choice of method and to the inclusion of controls for skill level or skill availability. These aggregate studies strongly support the view that firms seek locations with low wages, *ceteris paribus.*

Surprisingly, studies using project-level data do not typically find wages to be a significant determinant of location choice. An insignificant wage coefficient has been estimated in studies using foreign plant locations in the United States (Ondrich and Wasylenko 1993, Head, Ries, and Swenson 1999, List and Co 2000, and Keller and Levinson 2002); in Europe (Devereux and Griffith 1998, Head and Mayer 2004); and in China (Head and Ries 1996).

Indeed, in some specifications the estimated wage coefficient is positive.[5] A potential explanation for the failure to precisely estimate a negative wage coefficient is that wages and unobserved location characteristics may not be independent, leading standard econometric techniques that require exogenous covariates to produce biased estimates. To address this issue, Liu, Lovely, and Ondrich (2010) suggest the application of a control function approach to location choice studies.

As proposed by Berry (1994) to explain low price elasticity estimates in differentiated product studies, sellers will typically receive higher prices when their product has more desirable omitted characteristics. These omitted characteristics may include any attribute that affects the true value of the product to the buyer. When independence is maintained, buyers look less price-sensitive than they are because they receive more for the price they pay than the econometrician takes into account.[6] Applying this logic to the FDI context, omitted location characteristics that influence worker productivity and wages could lead to biased estimates of the wage sensitivity of investors. If the unobserved factors are otherwise mean independent of observed factors, there is unambiguously a downward bias in standard estimates—firms look less sensitive to the wage than they really are.

One approach to spatially correlated errors is to estimate a nested logit model (*e.g.,* Head and Mayer 2004).[7] A second approach, which is used in both conditional logit estimation and count data methods, is to control for time-invariant unobserved spatial characteristics with fixed effects (*e.g*., Head and Mayer 2004, Keller and Levinson 2002).[8] As demanding of the data as these procedures are, neither approach fully accounts for the omission of location characteristics correlated with the wage. It is difficult to control for unobserved location-specific attributes for several reasons. First, there may be insufficient variation over time or too many empty cells to use fixed effects defined over the same geographic unit as the choice set. Keller and Levinson (2002), in their study of foreign factory openings in U.S. states, Head and Mayer (2004), in their study of Japanese factory openings in regions within European countries, and Head and Ries (1996), in their study of FIE locations in Chinese provinces, use fixed effects defined over a geographic area larger than the unit of location choice.[9] A second reason that it is difficult to control for location-specific attributes is that these unobservables may vary with time. In the China, where liberalization advanced at a varied pace, beginning in the coastal provinces but then pushing westward and increasing in speed, the productivity of local factors changed over time and across provinces. One way to capture such time-varying unobservables is to introduce time-province fixed effects to the conditional logit. This approach typically is problematic, however, as it would introduce more than 100 additional parameters to the estimation.

An alternative two-stage method is proposed by Petrin and Train (2005 and 2006), based on control functions.[10] A control function is a term or factor added to an econometric specification to capture the effect of unobserved local characteristics, thereby breaking the correlation of the wage variable with the error term of the location-specific profit function. The use of control functions was pioneered by James Heckman (1976, 1979) to correct selectivity bias in normal linear regression models. The control function approach was later used in the analysis of the Tobit model by Smith and Blundell (1986) and in the analysis of the binary probit model by Rivers and Vuong (1988). Petrin (2005) and Petrin and Train (2005 and 2006) introduce the use of control functions to the estimation of conditional logit models.

Liu, Lovely, and Ondrich (2010) apply the control function method of Petrin and Train to firm-location choice. Their approach proceeds in two steps: in the first step, OLS regression is used to estimate the variables that enter the control function; in the second step, the likelihood function is maximized with the control function added in the form of additional explanatory variables. They find that coefficient estimates differ significantly across the corrected and the uncorrected procedures. Using a control function, they estimate a downward bias of 50-90% in wage estimates estimated with standard techniques. We adopt this technique in our estimation procedures, as a parsimonious and powerful way to correct for potential omitted variables bias.

III. The Location Choice Model

The Profit Function

A multinational firm seeks to invest one unit of capital in the form of an equity joint venture (EJV) somewhere in China.[11] The firm will locate its production of a differentiated good in the province that maximizes its profit.[12] As in Krugman (1980), Romer (1994), Rutherford and Tarr (2002) and Broda and Weinstein (2006), we associate varieties with country of origin. The firm produces with a generalized Cobb-Douglas technology, using variable inputs of labor, imported inputs, and a vector of intermediate (locally-provided) services. Log profits for a representative firm producing a variety of good *g* in province *j* can be written as:

$$\ln \pi_{gj} = \ln(1-\tau_j) + \ln(p_{gc} - c_{gj}) + \ln D_{gc}, \qquad (1)$$

where τ_j reflects the (perhaps concessionary) tax rate on foreign investment in province *j*, p_{gc} is the price received by the representative firm producing the Chinese (*c*) variety of good *g*, c_{gj} is the unit cost of producing good *g* in province *j*, and D_{gc} is global demand for the Chinese variety of good *g*.

Because China is used as an export platform, the market for many of the goods produced by foreign-invested enterprises is national or global and does not vary by firm location within China. Let E_g denote global expenditure on all varieties of good *g*. Consumers allocate their expenditure across varieties by maximizing a constant-elasticity-of-substitution non-symmetric subutility function for each good, as in Broda and Weinstein (2006).[13] The demand for Chinese made varieties of good *g*, which depends on delivered prices for varieties from all producing countries, $C \subset \{1,...,N\}$, is:

$$D_{gc} = \frac{d_{gc} P_{gc}^{-\sigma_g}}{\sum_{n \in C} d_{gn} P_{gn}^{1-\sigma_g}} E_g . \tag{2}$$

The non-symmetric subutility function allows for idiosyncratic preference terms, d_{gc}, and resulting demand functions that differ by variety.[14] The elasticity of substitution among varieties of good *g* is assumed to exceed unity: $\sigma_g > 1$.

Each firm sets its price to maximize profits. Following Dixit and Stiglitz (1977), if the number of firms is large, firms treat the elasticity of substitution across varieties, σ_g, as if it were the price elasticity of demand. The resulting producer prices are markups over marginal costs: $p_{gj} = (\sigma_g / (\sigma_g - 1)) c_{gj}$.

To express the profitability of locating in province *j*, we begin by taking the natural log of (2) and substituting the resulting expression for log demand into (1). Note that when firms choose among locations in China, the only relevant information is the ordering of profits across provinces. Factors that do not vary across locations do not affect the ordering of profits and can be omitted. Subtracting these location-invariant factors from profits and denoting the resulting variable profits potentially earned in province *j* as V_{gj}, yields

$$\ln V_{gj} = \ln(1 - \tau_j) - \sigma_g \ln c_{gj} . \tag{3}$$

Cost is a function of provincial factor prices, the wage, *w*, the price of imported inputs, p_m, a price index for locally-provided inputs, p_s, and an idiosyncratic cost shock:

$$\ln c_{gj} = \theta_{gl} \ln w_j + \theta_{gm} \ln p_{mj} + \theta_{gs} \ln p_{sj} + e_{ij}^c, \quad (4)$$

where θ_{gk} denotes a cost share in industry *g*. Using (3) and (4), we obtain an expression for variable profits that expresses the profits of locating in a province as decreasing in factor prices and tax rates:

$$\ln V_{gj} = \ln(1-\tau_j) - \sigma_g \theta_{gl} \ln w_j - \sigma_g \theta_m \ln p_{mj} - \sigma_g \theta_s \ln p_{sj} - \sigma_g e_{ij}^c. \quad (5)$$

It is clear from (5) that the effect on potential variable profits of an increase in the provincial wage, *ceteris paribus*: (i) is larger for firms with a larger labor cost share, θ_{gl}; and (ii) is larger for firms facing a higher demand elasticity, σ_g. We use information on firms' location choices in China to estimate the sensitivity of these firms to wage differences across provinces, allowing for variation in this response by labor intensity and demand elasticity. Additionally, we allow for the possibility that the production parameters embedded in (5) differ according to the development level of the source country. Specifically, we estimate these parameters separately for OECD investors and for ECE investors.

Agglomeration and Local Suppliers

Previous research has shown that foreign firms have a strong tendency to locate in areas where other foreign firms have located. We incorporate agglomeration into our model by adapting the Head and Ries (1996) framework for localization economies. Head and Ries argue that agglomeration in China is the result of localization economies from concentrations of intermediate service providers. They assume that the market for local services is monopolistically competitive and that foreign firms use a composite of these services. They show how the equilibrium number of intermediate suppliers depends on the final-good price, the number of foreign firms to which they may sell, N_j^f, and the number of domestic firms who may undertake the costly upgrading necessary to serve foreign firms, $\bar{N}_j^s$. Dean, Lovely, and Wang (2009) use this framework to derive an intermediates price index for locally-provided service inputs. This index, p_s, appears in the profit function (5) and measures the price per effective service unit. Assuming log-linear functional forms, this index can be expressed as

$$\ln p_{sj} = \ln A + \mu_L \ln w_j + \mu_p \ln p_j + \mu_f \ln N_j^f + \mu_s \ln \bar{N}_j^s, \tag{6}$$

where *A* is a constant and the coefficients are functions of the underlying final-goods and intermediates production parameters. Substituting this expression back into the firm's profit function (5) yields an expression that can be used as the basis for estimation.

Benchmark Estimating Strategy

Our basic estimating strategy is similar to conditional logit procedures in previous studies. We treat these conditional logit results as a benchmark for comparison to results obtained using the control function method. The profit function (5) and the price index (6) yield a linear function for log profits with arguments given by the vector

$$\mathrm{X} = [\ln w, \ln p_m, \ln(1-\tau), \ln N^f, \ln \bar{N}^s, \ln I]. \tag{7}$$

Letting the error vector $e = \sigma_g e^c$, we obtain $\Pi = \mathrm{X}\beta + e$, where β is the vector of parameters to be estimated. Our estimation strategy depends on the distribution of the unobserved idiosyncratic terms, e_{ij}. If these features are distributed independently according to an extreme value distribution, then the probability, P_k, that province *k* is chosen, where *k* is a member of choice set *J,* is given by

$$P_k = \frac{\exp(x_k \beta)}{\sum_{j \in J} \exp(x_j \beta)}. \tag{8}$$

This conditional logit is well suited to the location choice framework since it exploits extensive information on alternatives, can account for match-specific details, and allows for multiple alternatives.[15] Regional fixed effects are added to the list of regressors to capture regional correlation in supply and demand shocks.

As suggested by the variable profit function (5), the effect of a higher wage will vary with the skill intensity, final-good demand elasticity, and technology level of the firm. To test for varying parameters, we interact the provincial wage with firm characteristics. The first characteristic we interact with wage is a measure of skill intensity based on the average wage paid by the industry in 1995. Data on average wages by industry is drawn from the Third Industrial Census, a complete census of formal economic activity in China. Correlations of the average wage with two measure of industrial skill intensity, science and technology expenditures as a share of value added in 1995 from Chinese firm-level data and the ratio of non-production to production workers in the corresponding US industry, are high.[16] We use the average wage instead of these alternative measures because it is based on Chinese data, and measured with less error than the science and technology share as it is based on a much larger, broader sample of firms. We expect that firms in industries with higher average wages, and thus relatively small shares of unskilled workers, will be less responsive to provincial wage differentials.

The second industry characteristic we interact with the provincial wage is the US import demand elasticity for Chinese made goods, estimated by Broda and Weinstein (2006) for 3-digit industries over the period 1990-2001.[17] We expect that firms in an industry facing higher import demand elasticity will be less able to pass wage costs onto consumers and, thus, will be more sensitive to provincial wage variation. Finally, to permit industry parameters to vary by source country, we estimate our conditional logits using three samples: the full sample, projects funded from ECE sources and projects funded from foreign, primarily OECD, sources. [18]

The Control Function Approach

Despite the inclusion of regional fixed effects, possible endogeneity of the wage remains and can be illustrated by specifying the error in the profit function as a two-component error:[19]

$$\varepsilon_{ij} = \beta_{\xi}\xi_j + e_{ij}. \tag{9}$$

ξ_j is location specific, observed by workers and firms but not by the researcher. e_{ij} is a firm-specific idiosyncratic error, assumed to be independent across firms and locations. Defining $\mathbf{X}_j$ as in (8) and letting Z_j be the instrumental variable, under certain regularity conditions the log wage can be expressed as an implicit function of all factors taken as given at the time of the decision:

$$\ln w_j = \ln w_j(\mathbf{X}_j, Z_j, \xi_j). \tag{10}$$

Because wages will be higher in locations with more desirable omitted characteristics, ε_{ij} and $\ln w_j$ will be correlated even after conditioning on $\mathbf{X}_j$, violating the weak-exogeneity requirement for conditional logit covariates and leading to inconsistent parameter estimates.

Petrin and Train (2005 and 2006), illustrate how a control function can be used to test for and correct the omitted variables problem. The method proceeds in two steps. The first step is a linear regression of log wages ($\ln w_j$) on exogenous variables $\mathbf{X}_j$ and Z_j using provincial level data across years. We use this regression to construct the expected wage for each province in each year. The residual is used to form the control function, $f(\mu_j, \lambda)$, where μ_j is the disturbance from the first-stage regression and λ is a vector of estimated parameters. The profit function for firm *i* locating in province *j* can now be written as

$\ln \pi_{ij} = \alpha + \mathbf{X}_{ij}\beta + f(\mu_j, \lambda) + (\beta_\xi \xi_j - f(\mu_j, \lambda)) + e_{ij}$. The new error, $\eta_{ij} = \beta_\xi \xi_j - f(\mu_j, \lambda) + e_{ij}$, includes the difference between the actual province-specific error $\beta_\xi \xi_j$ and the control function, plus the idiosyncratic error. As described in Appendix A, we use bootstrapping methods to correct the reported errors.

Therefore, we assume that at location *j* the log wage, $\ln w_j$, can be expressed as:

$$\ln w_j = E(\ln w_j \mid \mathbf{X}_j, Z_j) + \mu_j(\xi_j) \quad ,$$

where $\mu_j(\xi_j)$ is one-to-one in ξ_j. Including $f(\mu_j, \lambda)$ in the conditional logit specification holds constant the variation in the error term of the location-specific profit function that is not independent of the wage. The equation for $\ln w_j$ above implies that $\hat{\mu}_j$ can be constructed as the residual from a first-stage regression of $\ln w_j$ on $\mathbf{X}_j$ and Z_j.

This approach requires an instrument for the first-stage wage regression that is correlated with the wage paid by EJVs, but uncorrelated with foreign firms' location choices, conditional on other exogenous variables. As in Liu, Lovely, and Ondrich (2010), our first-stage regression is a reduced-form wage equation with controls for labor supply (*e.g*. population, share of labor force with secondary education or more) and for labor demand (*e.g*. the rate at which output of state-owned enterprises is falling, cumulative foreign investment, and the number of local enterprises). The log of average industrial wage paid by state-owned enterprises (SOEs) is used as Z_j. Liu, Lovely and Ondrich provide justification for the assumption that private-sector wages are influenced by some provincial characteristics that drive multi-factor productivity, while SOE wages are not. They rely on the administrative SOE wage setting process and SOE productivity-wage gaps to argue for the independence of SOE wages from unobserved factors that drive foreign-firm productivity.[20]

Figure 1 illustrates the relationship between the average SOE wage and the private wage during 1992-1995. The SOE wage tends to be high where the private wage is high, but the gap between them varies widely across provinces and regions. The unconditional figures illustrate gaps that are larger in provinces with the longest tradition of market orientation, as in the central and coastal regions, with smaller and even negative gaps in the remaining areas.

IV. Data Description and Sources

The sample of equity joint venture investments was compiled by Dean, Lovely, and Wang (2009). The sample contains EJVs undertaken during 1993-1996 using project descriptions available from the Chinese Ministry of Foreign Trade and Economic Cooperation (MOFTEC).[21] Provinces are grouped into five regions: coastal, northeast, central, southwest, and northwest.[22] Figure 2 shows that both ECE and foreign partners engage in equity joint ventures in all provinces. Investment into the southern coastal region is predominantly Chinese, reflecting the geographic proximity and early opening of these provinces. Investment in the northern coastal region is split more equally between both sources. The most prominent specialization occurs in the northwest region, where natural-resource based activities dominate. Ningxia has only low and medium skilled EJVs and Qinghai has only low skilled EJVs.

Our theoretical framework implies the use of the covariate vector $\mathbf{X}_j$ given by (7). Complete descriptions and sources for all variables are provided in Table 1. The *Chinese Statistical Yearbook* (various years) was used to compile data on labor supplies, agglomeration, intermediates suppliers, infrastructure and incentives. Summary data for provincial characteristics are provided in Table 2.

The wage measure is the average annual wage paid by private and foreign enterprises, drawn from Branstetter and Feenstra (2002). We also draw from Branstetter and Feenstra the average annual wage paid by state-owned enterprises, which we use as a first-stage instrument.[23] Wage measures are deflated by a national price deflator to create an average annual real provincial wage. Average wages do not control for provincial variation in labor quality, so we also include in the conditional logit analysis the share of the provincial labor force that has completed senior secondary school or above.

We do not have direct measures of the cost of imported inputs (p_m) nor the corporate tax rate (τ). To control for provincial variation in these factors, we include an incentive dummy that takes a value of one if there is a special economic zone (SEZ) or open coastal city (OCC) in the province. This variable does not vary during the 1993-1996 period. We also include a measure of provincial infrastructure, which influences the local cost of imported inputs. Telecommunications infrastructure is proxied by the number of urban telephone subscribers relative to population.

The number of foreign firms (N^f) is measured as the real value of cumulative FDI, which we refer to as agglomeration, for the period 1983 to the year before the project is undertaken. Availability of potential suppliers of intermediate goods $(\bar{N}_S)$ is measured by the number of domestic firms. This measure was created by Dean, Lovely, and Wang (2009), who take the total number of enterprises at the township level and above (thereby capturing larger enterprises that may have the capacity to supply a foreign-invested plant) and subtract the number of enterprises that are wholly or partly foreign owned.

To control for market demand, we include the population of the province and several measures of provincial income. The income measure is the size of the provincial private market, calculated as the private share of output multiplied by provincial GDP. We use non-state output to gauge the size of the market open to foreign enterprises because domestic sales in a province will be limited if demand is substantially satisfied by the state sector. Additionally, to allow for a flexible form for this market measure, we include the square of this variable. Sales may also be affected by the extent to which a province is liberalizing, so we include the change in state ownership, measured as the difference in the share of industrial output produced by SOEs between time *t* and time *t*-1.

V. Results

Benchmark Results

Table 3 reports the results of conditional logit estimation without control function, for the full sample, the ECE subsample and the foreign subsample. All variables are lagged one year to represent predetermined information, available to an investor at the time of the location decision. The first three models report results estimated without including any interactions of the wage and industrial characteristics. All covariates have the expected signs and all except agglomeration in the foreign sample are highly significant even in the presence of regional fixed effects. The regional coefficients indicate that EJVs are more likely to locate in any region other than the Southwest (the default category), although the difference is not significant for the Northwest region. As expected, these coefficients are largest for the Central and Coastal zones, which have received the largest share of foreign investment. The overall fit of the equation is good and comparable to other studies using similar procedures (*e.g.* Head and Ries 1996, Head and Mayer 2004). As seen in the first model, the wage coefficient is negative for the full sample and precisely estimated.

Detailed descriptions of Chinese inward investment describe ECE investment as locating in China to use it as a low-wage export platform. In contrast, investment from Japan, Europe, and the United States is characterized as locating in China to serve local markets.[24] This distinction is viewed as consistent with the greater clustering of ECE-funded ventures, which are less evenly distributed across provinces than is investment from Japan and the United States.[25] Moreover, evidence provided by Huang (2003) indicates that although ECE and foreign investments are similarly distributed across industries, foreign-funded firms make more intensive use of engineers, managers, and college graduates than do ECE-funded firms.[26] This suggests that even within 4-digit industries there are factor intensity differences associated with source country. For these reasons, we investigate the extent to which these two types of investors differ in their response to wages.

As shown in the second and third models of Table 3, the probability of an ECE or a foreign investor locating in a given province is negatively affected by the provincial wage and this response is highly significant for both groups. The coefficient estimate for the foreign sample, however, is significantly larger than it is for the ECE sample, -1.79 vs. -0.659. Thus, although both types of investors are responsive to the wage, the foreign sample appears to be more deterred from investing in provinces with relatively high wages. Greater wage sensitivity by foreign-funded ventures may reflect a heavier weight placed by these investors on explicit business costs, and less on personal connections, in choosing a location. OECD investors' lack of family and business ties to specific provinces may allow these investors to be more sensitive to location wage differences. The clustering of overseas-Chinese funded export activities, rather than being evidence of single-minded attraction to low-wage havens, as it is often depicted, may instead be explained by an expectation of personal connections to protect and promote business interests.[27] Some supporting evidence for this view is the larger weight placed by ECE investors on past investment, indicative of production clusters: the estimating coefficient for the agglomeration measure is 0.4 for ECE investors but about a third of that magnitude, 0.141, for foreign investors. ECE investors also place a lower weight on local firms, the skilled labor share in the province, and designation of the province as an SEZ or OCC, also consistent with the view that these investors have access to nearby production networks and local, personal connections not accessed by OECD investors.

Based on our theoretical framework, we expect higher wages to have a larger effect on profits in labor-intensive industries and, thus, we expect these industries to be more responsive to provincial variations in labor costs when choosing a location for a joint venture. Because much of the equipment used by foreign invested firms is imported, their largest local factor costs are for skilled and unskilled labor. To allow for a differential response to wages we interact the provincial wage with a measure of industry skill intensity, expecting a more elastic response in industries that are unskilled-labor intensive. To explore the hypothesis that competition for Northern markets influences firms' wage sensitivity, we also interact the wage with the US import demand elasticity for goods made in China. Following the logic of our theoretical model, we expect the coefficient on an interaction of the wage and the import elasticity to be negative—high price elasticity and, thus, more pressure on wage costs. To isolate the effect of market competition from factor intensity, we control for both skill intensity and product market conditions simultaneously.

We find strong evidence that the attraction of low wages is a function of factor intensity. As shown in the last three models of Table 3, the interaction of log wage and skill intensity is positive and highly significant, as predicted, for the full sample and for each subsample. The estimated coefficients for the subsamples indicate that OECD investors are more responsive to wages, even controlling for skill intensity of the industry. This difference between investors is largest for the most labor-intensive activities. For example, *ceteris paribus*, the estimated wage coefficient for OECD investors in the footwear industry is -1.57, three and a half times larger than the estimated coefficient for ECE investors, -0.45.[28] Both estimates are precisely estimated.

When we account for variation across industries in demand conditions, these differences across investor types remain. As shown in the fourth column of Table 3 for the full sample, higher demand elasticity is associated with a greater aversion to high wage provinces: the coefficient on the interaction of wage and import demand elasticity is -0.298 and highly significant. The negative sign on the wage-and-demand-elasticity interaction is consistent with the hypothesis that firms facing highly competitive conditions in import markets are less able to absorb higher wages by passing them along to foreign customers. When the sample is split into investor groups, as shown in the fifth and sixth models, demand conditions are significant influences on wage sensitivity for both groups but the estimated coefficient for the foreign sample is larger than it is for the ECE sample, -0.369 versus -0.252. Accounting for this differential response to product market competition widens the gap between ECE and foreign responses: including this interaction, the estimated wage coefficient for OECD investors in the footwear industry is -2.46, compared to the estimated coefficient for ECE investors, -1.06. Again, these estimates are precisely estimated. As in the models without wage interactions, we find that ECE investors place a higher weight on prior investment, but a lower weight on local firms, the skilled labor share, and designation of the province as an SEZ or OCC than do foreign investors.

Despite the positive coefficient for the interaction of wages and skill intensity, foreign investors are more responsive than ECE investors to wages regardless of industry. At the mean skill intensity and mean demand elasticity, the wage coefficient for foreign investors is -2.01, while for ECE investors this coefficient is -0.76. Differences between the two groups diminish somewhat as the skill intensity of the industry rises, but foreign investors remain more responsive. For example, the wage coefficient for the most skill-intensive activity (petroleum refining) is larger for foreign investors (-1.26) than for ECE investors (-0.29), despite the larger and positive foreign coefficient on the skill-wage interaction.

These findings illuminate difference among investors that are often drawn by reference to anecdote. Because ECE investors are more intensely engaged in activities that use China as an export platform, wage pressures are often depicted as more intense for them than they are for other investors. Indeed, in their discussion of competition among low-wage countries for export-platform FDI, Ross and Chan (2002) specifically address the wage pressures exerted on Chinese workers by South Korean, Taiwanese, and Hong Kong firms that subcontract to do labor-intensive manufacturing on the mainland. Our results suggest that OECD investors consider low wages as much or more than do ECE investors, at least at the time that the host province is chosen. Of course, our findings do not speak to possibly significant differences across investor groups in working conditions once the investment has been sunk.

Control Function Results

Table 4 provides results estimated using the control function approach as well as regional fixed effects. The reported standard errors (as well as variance matrices used in the testing of joint hypotheses) were corrected using a bootstrapping technique described in the appendix. The appendix also provides the first-stage regression results. This regression explains 86 percent of the variation in the private wage and the coefficient of the log of the SOE wage is highly significant, with a t-statistic of 9.07. Adding the log of the SOE wage to the first stage explains an additional 5 percent of the variation in private wages.

Looking first at the models without wage interactions, when the residual from the first-stage wage regression is added to the conditional logit as a control function, its coefficient is positive and significant at the 1 percent level. Petrin and Train (2005) interpret the significance of the control function as a test for omitted variable bias. The significance of the residual, therefore, indicates the presence of omitted variable bias in the uncorrected estimates. When the residual is added, the wage coefficient remains negative and highly significant, in the full sample and both subsamples. However, it increases substantially in absolute value, providing an estimate of the downward bias in the standard method, consistent with findings reported in Liu, Lovely, and Ondrich (2010). The coefficient of -2.079 estimated with the control function for the full sample is more than twice as large in absolute value as the coefficient of -0.949 estimated without the control function. Among other estimated coefficients, only the inferences drawn for the agglomeration measure are affected by the addition of the first-stage residual and only for the foreign sample. With the control function, foreign investors' location decisions are significantly and positively related to prior foreign investment. Inferences from other estimated coefficients are unchanged by the addition of the control function.

Table 4 also provides models that include the control function and interactions of skill intensity and demand elasticity with the provincial wage. As seen for all three samples, both interaction terms remain highly significant. Moreover, as in the models estimated without the interactions, the total effect of an increase in the wage on the probability is larger when the control function is included. For example, at the mean values for the skill intensity and the demand elasticity, the estimated wage coefficient for the foreign sample is -3.23 (compared to -2.01 without the control function) and for the ECE sample is -1.73 (compared to -0.76). Thus, we conclude that both sets of investors respond elastically to the wage, with foreign investors almost twice as sensitive.

Because these models include interactions involving the wage, we form the control function by including interactions between the first-stage residual and the two industrial characteristics. As seen in Table 4, these terms are not all individually significant. However, testing whether both of the two related coefficients are zero requires a joint hypothesis test. We present the value of the Wald χ^2 in the row labeled "CF Wald Statistic." The Wald Statistic is significant at the 1 percent level in all three samples. These results reinforce the indication of omitted variable bias present in the models that omit the wage interactions.

Table 5 provides estimated own and cross wage elasticities, by province. The elasticities of province j were calculated as in Greene (2003) by $\sigma_j^{own} = \beta^w(1-P_j)$ and $\sigma_j^{cross} = -\beta^w P_j$ where β^w and P_j are the estimated wage coefficient and predicted probability that an investor chooses province j. The table shows elasticities calculated using a control function. Looking across locations, the own-wage elasticity is smallest for those provinces with the highest predicted probability of being chosen, including Beijing, Guangdong, and Jiangsu. These provinces, conversely, have the largest predicted cross-wage effects, implying that a decrease in their wage has a larger effect on other provinces than the effect other provinces have on them. These estimates imply a dynamic that differs somewhat from the view expressed by Chan (2003), who fears that coastal provinces maintain low wages for private employers to fend off competition from interior provinces. Our estimates indicate that coastal provinces have less incentive to behave in this manner than do interior provinces; coastal provinces are less likely to lose investment to other provinces when their wages rise. However, our estimates also imply that these provinces have the largest effect on other province's chances of attracting investment if they do attempt to keep wages low.

As discussed in the introduction, foreign investment typically flows into particular sectors, shifting the pattern of production toward these favored sectors. To consider how shifts in production composition might change the elasticity of demand for domestic labor, we calculate the average estimated own-wage elasticities for each industry, for both the ECE and the foreign samples, as shown in Table 6. Comparing the last two columns, we see that the foreign elasticity is larger than the ECE elasticity for every industry, but both subsamples produce a similar ranking across industries. Some interesting differences emerge when we look at these rankings. In comparison to the own-wage elasticity calculated at the mean, industries with an average response to wages include leather, beverages, and printing. In the mid 1990s, however, industries with very large shares of total exports are among those industries with above average sensitivity to the wage, which is consistent with their rapid development in China after the liberalization of FDI rules in 1992.[29] These industries include footwear, wood products, textiles, and food. However, over the following decade, Chinese exports grew strongly in sectors with below average sensitivity to the wage, particularly professional, scientific, and controlling equipment, electrical machinery, and non-electrical machinery. That China was able to shift its export profile so quickly away from the most footloose and labor intensive sectors toward sectors that are less responsive to wage differences is worthy of further study. This shift is likely to have significant consequences for Chinese labor markets. Certainly, these findings suggest that the wage pressure to which an individual worker is subject depends on his or her industry-specific skills. Similarly, local labor forces are subject to different wage pressures, depending on the natural advantages of the local area.

VI. Simulation of a Wage Subsidy for Inland Provinces

In an attempt to increase employment and wages in inland provinces, the Chinese government now encourages foreign investment away from coastal locations. We use our estimated coefficients to simulate a wage subsidy for inland provinces. This simulation provides a window into the potential for policy-induced shifts in investment location and it allows us to predict which industries would be most likely to move inland. The appendix describes the methods we use to undertake the simulation. We perform a dynamic simulation in that we permit endogenous investment changes to alter the stock of foreign firms and, thus, the agglomeration effect in subsequent years, a simulation procedure emphasized by Head and Ries (1996).

Dynamic simulation results are presented in Table 7. We consider both a 10 percent and a 25 percent wage subsidy to foreign investors for projects located in any region other than the coastal region. Values given in the table indicate the percentage change in the total amount of investment flowing to a given province relative to our baseline simulations (no wage subsidy). Our findings indicate that firm location is quite elastic in that substantial increases in foreign investment flows into inland provinces can be obtained through a wage subsidy policy.

Provinces in the coastal region, which we assume receives no subsidy, lose investment. However, for the 10 percent wage subsidy the flow diminishes only 6 to 14 percent, depending on the particular province. When we increase the intervention to a 25 percent wage subsidy, however, coastal FDI shrinks between 25 percent and 31 percent. Thus, policy does appear to be effective in shifting investment away from these more prosperous and productive areas.

For the inland provinces, a wage subsidy can raise the FDI stock substantially. For the Central region, a 10 percent wage subsidy increases the stock of foreign investment by 19 to 34 percent and a 25 percent wage subsidy increases foreign investment by 65 to 85 percent. These impacts are similar for other inland regions and indicate that a wage subsidy could lead to substantially larger accumulations of foreign capital in these areas, perhaps contrary to the view that these areas are unattractive to many industries.

The subsidy policy affects the composition of the foreign capital stock as well as the amount. We calculate the change in the average skill intensity and the average import demand elasticity facing foreign investors in each province, under the 10 percent wage subsidy policy. These calculations indicate that the wage subsidy raises the average skill intensity and lower the average demand elasticity of investors who remain in the non-subsidized coastal region. At the same time, the average skill intensity of inland investors falls while the average demand elasticity rises. As expected, it is the most responsive investors for whom the wage subsidy prompts an alternative choice of host. Surprisingly, though, given the relatively large shifts we observe in the simulation, these changes in the character of investment are very small, with neither industrial characteristic changing more than 1 percent on average.

VII. How Wages Matter and to Whom

We are aware of no other econometric analysis of how product market competition influences the wage sensitivity of foreign investors. Our results support the view that competition for Northern markets influences the weight placed on potential host wages by foreign investors. While we cannot control directly for the share of output that investors expect to export to Northern markets, our interaction of host wages with the Broda-Weinstein U.S. import demand elasticities allows a window into a previously unexamined link between FDI location choice and competition for rich country markets. We find that all investors are sensitive to U.S. market conditions when locating their manufacturing facilities in China, as their wage sensitivity varies significantly with the US import demand elasticity. This variation matters, even when we control for the skill intensity of the industry.

In general, observed outcomes reflect complex calculations by firms faced with host-country differences along many dimensions that influence business costs. Using the control-function approach to control for unobserved attributes of potential hosts, we find that firms' response to wages is elastic. There are significant differences among firms, however, consistent with the existence of informal production networks and personal connections to particular regions. ECE investors appear to be less sensitive overall to wages in the host province. They also place greater weight on previous investment, much of it from ECE sources. Foreign investors, who are often characterized as serving the Chinese domestic market, are highly sensitive to local wages, but this responsiveness depends primarily on the skill intensity of the activity. For both groups, investors in unskilled-labor-intensive industries exhibit the most wage sensitivity in choosing a host. These results direct our attention to the role played in the development process by particular types of activities and they suggest that wage pressures on local hosts are influenced by their comparative advantage.

Appendix

First-stage Results and Bootstrapping Procedures

A maintained primitive of the control function approach is that wages are additively separable in the observed ($\mathbf{X}_j$ and Z_j) and the unobserved factors (ξ_j); the unobserved factors are mean independent of the observed factors. This assumption implies uncorrelatedness of unobservables and covariates. It enables use of linear regression in the first stage and ensures the consistent estimation of the residual in the first stage. First-stage results are shown in Table A1.

Table A1. First Stage OLS Regression: Dependent Variable is Log Private Wage

Variables	**Coefficient**	**Robust S.E.**
Constant	0.788	0.862
Log Agglomeration	0.101***	0.011
Log Local Firms	-0.020	0.029
Log Population	-0.121***	0.044
Skilled Labor Ratio	-0.008***	0.002
Log Telephone Density	-0.014	0.031
Log Private Market Size	0.111**	0.052
Squared Log Private Market Size	-0.022***	0.006
Change in State Ownership	-0.284	0.279
SEZ or OCC	-0.077	0.043
Regional Fixed Effects		
Central	0.059	0.043
Coastal	0.042	0.045
Northeast	-0.000	0.041
Northwest	-0.032	0.036
Log SOE Wage	0.846***	0.093
Number of Observations	196	
R^2	0.86	

Notes: "***", "**" and "*" denote significance levels at 1 percent, 5 percent and 10 percent respectively; variables are lagged by one year; Gansu and Tibet excluded.

When a control function that includes predicted values is added to the estimation, the coefficients are consistent but the standard errors are incorrect. Petrin and Train (2005b) use bootstrapping to correct standard errors in their applications. In the first stage, we bootstrap a wage sample and regress the private wage on the exogenous variables and the instrumental variable, the log of the SOE wage, for years 1990-1996.[30] The control function in the second stage is a function of the first-stage residual (and the interactions of the residual with other covariates when we use interactions of these covariates with wages). We run the conditional logit with this control function and repeat this process 100 times. The variances of these bootstrapped coefficients in the second stage are added to the traditional variance estimates from the conditional logit regression with the control function.[31] We experiment with different orders of the polynomial of the residuals to specify the control function, but typically, higher orders are insignificant and have only a small effect.

Simulation Procedures

Our simulations present static and dynamic estimates for the location choices of Chinese firms and for foreign firms, both with and without a wage subsidy to inland provinces. Letting *n* stand for the source category of the firm, we have $n = C$ or $n = F$. Years are indicated by the variable *t*, and the first year of our simulation is $t = 1993$. The first input to our analysis is a relative frequency function or empirical density function for the *I* industries, indexed by *i*. This relative frequency function depends on both *n* and *t*, and is obtained from our sample, as no information on industry distribution of all projects exists in the China Statistical Yearbooks or other sources. Thus, the first input to our analysis takes the form:

$$f_{nt}(i), \quad i = 1, \ldots, I; \quad n = C, F; \quad \{t \mid 1993 \le t \le 1996 \cap t \in \mathbf{Z}^+\},$$

where

$$\sum_{i=1}^{I} f_{nt}(i) = 1, \quad n = C, F; \quad \{t \mid 1993 \le t \le 1996 \cap t \in \mathbf{Z}^+\}.$$

The second input to our analysis is, for each *n*, the number of new industrial projects in year t, V_{nt}. While Yearbook numbers are available for total contracted investment and the number of projects by year, as well as the total realized direct foreign investment by year, there is no data on the realized industrial projects by year by source. We estimate these numbers, using data on total investment flows and other information from the China Statistical Yearbooks.

We begin with the total amount of foreign capital actually utilized, by year, from various issues of the China Statistical Yearbooks. To estimate the amount of actually utilized foreign investment into the industrial sector, we scale total investment in each year by average share of contracted foreign investment that flows to the industrial sector, 68.9% (China Statistical Yearbook, 1997). We then split this utilized industrial foreign investment between our two sources, ECE and Foreign, using the average share of investment from Hong Kong, Macau, and Taiwan over the 1985-1996 period, 66.4% (China Statistical Yearbook, 1997).

To estimate the number of projects represented by this estimated utilized foreign investment in the industrial sector, we use information on total contracted investment and the number of contracted projects by year to compute the average value of projects in each year (China Statistical Yearbook, 1997). We then apply this average value to the estimated value of utilized foreign investment in the industrial sector, by source and by year, to calculate the estimated number of projects in the industrial sector, by source and by year.

No industrial distribution of projects by industry is available from Chinese Yearbooks. We, therefore, approximate, $V_{nt}(i)$, the number of projects by industry, by $V_{nt} f_{nt}(i)$. These values give us weights that we use to weight our simulation results to calculate the addition to FDI, year by year. The third input to our analysis is a representative firm for *n*, *i*, and *t*.

The algorithm for both the static and dynamic simulations starts with $t = 1993$. The covariates for all provinces are completely determined by *n* and *i*. Thus, for each province *j* and for each *n* and *i*, we use our estimated conditional logit parameters to construct the predicted probability $P_{ni,1993}(j)$ that the province is chosen by the representative firm for that *n* and *i*. The total number of new ventures locating in province *j* for given *n* and *i* is given by $P_{ni,1993}(j)$ times the weight for that *n* and *i* when $t = 1993$:

$$V_{n,1993} f_{n,1993}(i) P_{ni,1993}(j) \quad .$$

This method allows us to calculate the share of total projects for each *n* and *i* locating in province *j*. However, we still cannot compute the total real value of additional FDI for $t = 1993$. To get this, we need to compute:

$$A_{ni,1993} V_{n,1993} f_{n,1993}(i) P_{ni,1993}(j),$$

where $A_{ni,1993}$ is the average value per new venture for each *n* and *i*. This average value is calculated from the sample data.

The baseline proceeds by returning to the start of the algorithm and replacing $t = 1993$ with $t = 1994$. Once this is complete, we successively replace $t = 1994$ with $t = 1995$ and $t = 1996$. The static simulation for an inland wage subsidy is the same as the baseline except that wages are subsidized for inland provinces for each of the years at both 10 and 25 percent levels.

The dynamic simulation methods are similar to those for the static simulation for the year 1993. They differ, however, for the periods 1994 on because the value of cumulative FDI for province j in year t used in the probability predictions is computed as the sum of cumulative FDI for province j in year $t-1$ and $\sum_{n=C,F} \sum_{i=1}^{I} A_{ni,t-1} V_{n,t-1} f_{n,t-1}(i) P_{ni,t-1}(j).$

Endnotes

1 . Shifts in the relative demand for unskilled workers are highlighted in the trade-and-wages debate. Lawrence (2009) provides a recent evidence. Regarding increased labor demand elasticity, see Rodrik (1997) for argument and implications and Slaughter (2001) and Hasan, *et al* (2007) for evidence from a developed and developing country, respectively.

2 . Wang (2001) describes the formal legal system supporting FDI in China and examines in detail the role played by informal personal networks.

3 . Ehrenberg and Smith (2003) also describe the remaining two laws: the elasticity of labor demand is high when other factors of production can be easily substituted for labor, and when the supply of other factors is highly elastic.

4. The investment percentage is calculated by authors from Huang (2003), Table 1.1. The export share taken from Huang (2003), p. 18.

5. A recent exception to this pattern is Amiti and Javorcik (2005), who use a different technique. They relate changes in the number of foreign-invested firms in Chinese provinces to changes in the average wage.

6. Petrin and Train (2006) provide many examples from studies of differentiated product models, including the well-known study by Berry, Levinsohn, and Pakes (1995).

7. Further discussion of the application of these methods to modeling firm location decisions can be found in Ondrich and Wasylenko (1993).

8. As Head, Ries, and Swenson (1999) note, this provides a convenient way to capture common attributes. Many studies observe fewer than 1,000 investments and as they sometimes span a decade or more, there are few observations in many year-location cells. Consequently, parsimony is necessary given data limitations.

9. Keller and Levinson (2002) control for time-invariant state characteristics in their analysis of the value of foreign-owned gross property, plant and equipment but are limited to the use of regional fixed effects in their analysis of planned foreign-owned factory openings.

10 . Berry, Levinsohn, and Pakes (1995) develop an approach that is similar in spirit to the inclusion of fixed effects for each choice unit, but which recognizes the need for parsimony. This approach, known as the product-market control approach, has been widely used in estimating differentiated product models. It involves estimation of a set of controls that match observed to predicted markets shares. Petrin and Train (2006) identify a number of advantages of this approach, but note that sampling error in market shares enters the estimation equations in a non-linear manner. Unless sampling error in the market shares is minimal, this estimator is not consistent and asymptotically normal.

Because the sampling error is unknown for the data we employ in the present study, we choose not to use the product-market control method.

11. During the span of this study, significant restrictions on wholly-owned subsidiaries were in place and equity joint ventures were the dominant mode of entry for foreign investors.

12. We condition on the decision to produce in China. We also use a static model of the investment decision, as is common in the literature.

13. An alternative to the assumption of global market demand is to follow Head, Ries, and Swenson (1999) and assume that demand facing the representative firm locating in province *j* depends on price, local income I_j, and an idiosyncratic demand shock: $\ln D_j = \eta_I \ln I_j - \eta_p \ln p_j + e_{ij}^d$. In our empirical work, we test the sensitivity of our results to this alternative form for demand.

14. See Broda and Weinstein (2006, p. 556-8) for a discussion of the non-symmetric CES function and resulting demand functions. Their methodology relies on Feenstra (1994).

15. An alternative approach is to use count data with a Poisson or negative binomial specification. These count data approaches are appropriate when there is a preponderance of zeros and small values for counts (Greene, 2003). U.S. data used by Keller and Levinson (2002) have this characteristic but the Chinese data do not.

16. We thank Gary Jefferson for making the Chinese S&T shares available to us as well as the size of the samples on which they are based. These data were concorded from Chinese industrial codes to ISIC by the authors. US data on skill ratios is drawn from the NBER-CES Manufacturing Industry Productivity Database for 1995, concorded from SIC to ISIC by the authors. The mean skill intensity for the projects in our sample is 0.45.

17. US import elasticity estimates were downloaded from files made available at http://faculty.chicagobooth.edu/christian.broda/website/research/unrestricted/TradeElasticities/TradeElasticities.html. The data were concorded from SITC 3-digit to ISIC 3-digit industries by the authors.

18. Grouping of projects into ECE and foreign is described by Dean, Lovely, and Wang (2009). The ECE designation includes those with a partner from Hong Kong, Macao, Taiwan, Malaysia, Indonesia, and the Philippines, with the first three accounting for 87 percent of the total identified with these countries. Foreign partners are those from other sources, with the largest shares from the United States and Japan.

19. This discussion adapts the discussion of consumers' choice among differentiated products in Petrin and Train (2006) to the location choice context.

20 . In China, SOE wages prior to 1996 were largely determined by the central government, despite several rounds of wage reforms. Starting in 1985, the Ministry of Labor (MOL) provided some incentives to SOEs, but to a very limited extent. Deeper reforms of China's SOE wage structure were not implemented until the Ninth Five Year Plan (1996-2000). Therefore, during the span of our sample, SOE wages were largely set by central government guidelines and were largely unresponsive to changes in private-sector productivity. Evidence from SOE productivity-wage gaps also supports the view that SOE wages do not reflect local attributes that influence firm productivity. Parker (1995) finds that, "In 1992, state industrial wages were 43 percent higher than those available in urban collectives, and only 22 percent below those of the other ownership forms; these workers in other ownership forms, however, were 130 percent (in 1990 prices) to 200 percent (in 1980 prices) more productive than those under state-ownership."

21. Equity joint ventures are limited liability companies incorporated in China, in which foreign and Mainland Chinese investors hold equity. For further details, see Fung (1997). Wang (2001) provides additional details on the legal framework for foreign investment.

22. Coastal: Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang; Northeast: Heilongjiang, Jilin, Liaoning; Central: Anhui, Henan, Hubei, Hunan, Jiangxi, Shanxi; Northwest: Gansu, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Tibet, Xinjiang; Southwest: Guangxi, Guizhou, Sichuan, Yunnan.

23. Banister (2005) discusses problems in Chinese labor statistics of geographic coverage, non-wage compensation, and under-reporting

24. This distinction is drawn by Henley, Kirkpatrick, and Wilde (1999).

25. Huang (2003) provides the standard deviation values for project number and value, by source (p40, n67).

26. See especially Huang (2003), Table 3.3, p. 134.

27. Such expectations are supported by extensive interviews summarized in Wang (2001).

28. Values for skill intensity and import demand elasticity are given in Table 6.

29 . Dean and Lovely (2010) provide Chinese export shares for 2005 and 1995.

30. We do not use years after 1996 in the first stage to avoid possible structural changes in wage structure after 1996 due to SOE reforms. We also do not use years before 1990 for similar concerns. Years after 1989 and before 1993 are kept to increase the sample size and the reliability of bootstrapping. However, the direction and magnitude of bias is consistent when we experiment with different years in the first stage.

31. Karaca-Mandic and Train (2003) propose alternative standard error correction procedures, but find results very similar to bootstrapping.

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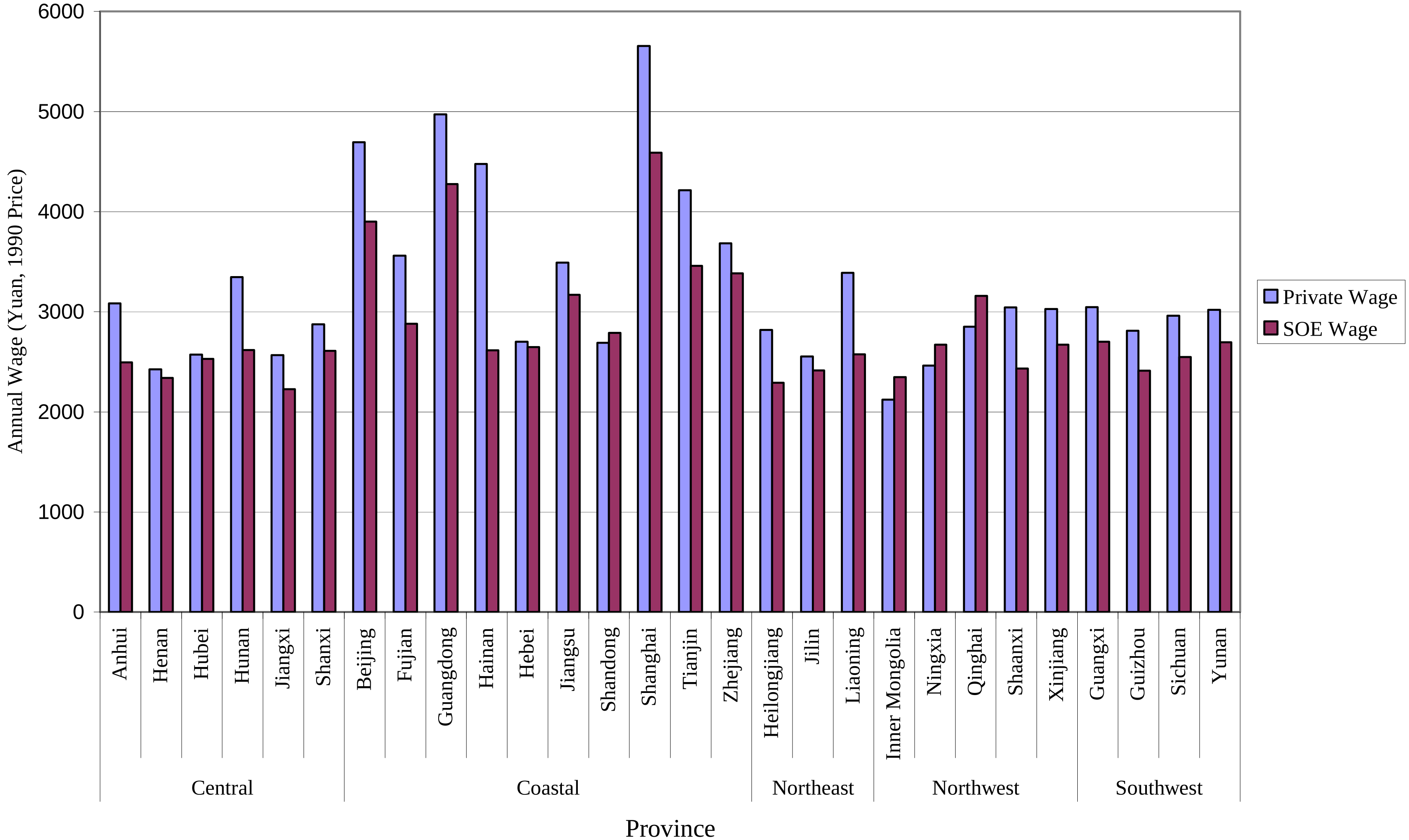
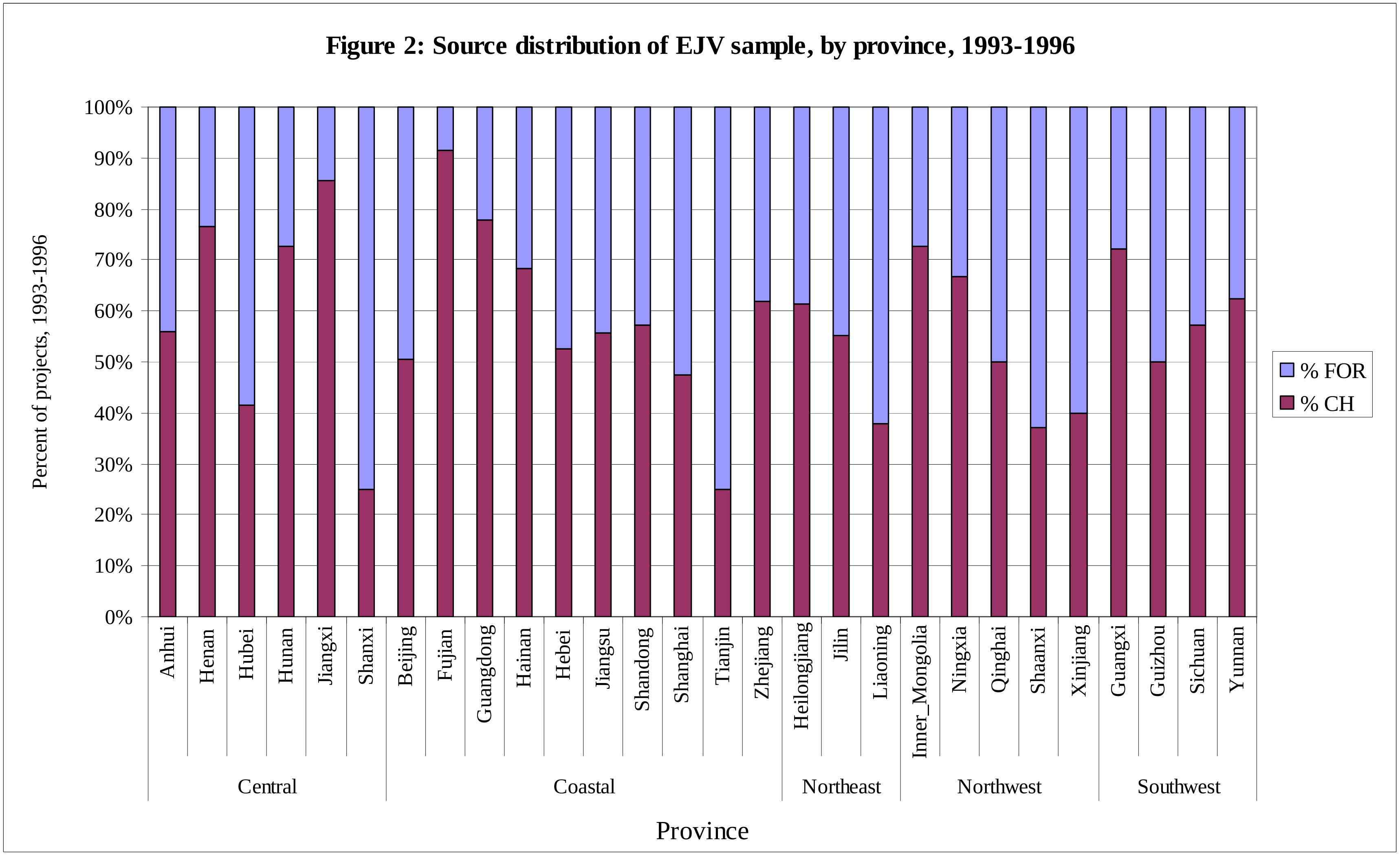
Figure 1: Average private wage and average SOE wage, by province, 1992-1995





Source: Dean, Lovely, and Wang (2009)

Table 1. Data Definitions and Sources

Variable	Definition	Source	Mean*
EJV project:			
Location	Province	*Almanac of China's Foreign Economic Relations and Trade*, various years, Dean, Lovely and Wang (2009)	
Source	ECE=Macao, Taiwan, Hong Kong, other South Asian countries Foreign=all other countries		
Industry	3-digit ISIC Rev.2 classification		
SOE Wage	Average annual wage for industrial workers in state-owned enterprises, in 1990 yuan.	Branstetter and Feenstra (2002), from *China Statistical Yearbook*, various years	2837
Private Wage	Average annual wage for industrial workers in other enterprises (private, foreign, etc), in 1990 yuan	Branstetter and Feenstra (2002), from *China Statistical Yearbook*, various years	3254
Skill Intensity	Average annual wage calculated as total industrial wage payment divided by total industrial employment, concorded to ISIC 3-digit classification	China Industrial Census, 1995	6175
US Import Demand Elasticity	US import demand elasticity, based on 1990-2001 data, concorded by authors	Broda and Weinstein (2006)	3.88
Agglomeration	Cumulative value of real contracted FDI, from 1983 until *t*-1, in millions of 1980 U.S. dollars	Coughlin, et al. (2000)	1536
Local Firms	Number of SOE and collective industrial enterprises at the township level and above	*China Statistical Yearbook*, various years, Dean, Lovely and Wang (2009)	16061
Population	Province population, in millions	*China Statistical Yearbook*, various years	41
Skilled Labor Ratio	Share of population who have a senior secondary school education level or above (in percentage points)	*China Statistical Yearbook*, various years and calculations by authors	12.08
Telephone Density	Number of urban telephone subscribers per million persons	*China Statistical Yearbook*, various years	29266
Private Market Size	Real Provincial GDP x (1–SOE share), where SOE share is the production share of SOEs; GDP is value in billions of 1990 yuan	*China Statistical Yearbook*, various years, and calculations by authors	57
Change in State Ownership	Difference between shares of industrial output from SOEs in year *t* and *t*-1	*China Statistical Yearbook*, various years, Dean, Lovely and Wang (2009)	-0.04
SEZ or OCC	Dummy variable for a province with SEZ or Open Coastal City	Dean, Lovely and Wang (2009)	0.43

*Descriptive statistics for provincial characteristics calculated from pooled data for 1993-1996 (excluding Tibet and Gansu).

Table 2. Provincial Characteristics, Period Averages (1993-1996)

	Annual Private Wage (1990 yuan)	Cumulative FDI (million 1980 US$)	Number of local firms	Population (millions)	Share of Skilled Workers	Phones per million persons	Output Share of SOEs	Private Market Size (billion 1990 yuan)
Anhui	3083	353	23000	59	7	13000	0.41	53
Beijing	4695	1981	7000	11	32	119000	0.51	34
Fujian	3561	4499	12000	32	8	28000	0.23	73
Guangdong	4970	13876	25000	67	11	47000	0.25	192
Guangxi	3045	933	11000	45	8	12000	0.50	37
Guizhou	2810	87	6000	34	6	6000	0.71	10
Hainan	4476	1336	1000	7	12	26000	0.53	9
Hebei	2701	566	21000	64	8	18000	0.38	82
Heilongjiang	2819	434	17000	37	15	30000	0.72	28
Henan	2426	450	20000	90	8	10000	0.40	83
Hubei	2574	704	23000	57	10	17000	0.49	58
Hunan	3346	475	23000	63	9	15000	0.48	54
Inner Mongolia	2122	78	9000	22	13	22000	0.68	13
Jiangsu	3489	4273	39000	70	12	27000	0.23	184
Jiangxi	2565	293	16000	40	8	12000	0.50	29
Jilin	2553	333	13000	26	17	33000	0.65	20
Liaoning	3390	2064	26000	41	14	37000	0.49	75
Ningxia	2462	11	2000	5	11	22000	0.74	2
Qinghai	2850	5	1000	5	11	17000	0.83	1
Shaanxi	3042	483	13000	35	12	14000	0.61	20
Shandong	2691	2929	25000	87	9	16000	0.30	160
Shanghai	5654	3514	9000	14	29	124000	0.46	65
Shanxi	2876	107	11000	30	12	17000	0.49	27
Sichuan	2960	759	37000	112	7	10000	0.44	94
Tianjin	4213	1039	8000	9	22	65000	0.41	26
Xinjiang	3027	64	6000	16	14	20000	0.71	12
Yunrjan	3021	113	7000	39	5	11000	0.73	16
Zhejiang	3684	1251	36000	43	9	32000	0.19	127

Table 3. Models Without Control Functions

	Wage Variable Without Interactions			Wage Variable With Interactions		
	Full Sample	**ECE Subsample**	**Foreign Subsample**	**Full Sample**	**ECE Subsample**	**Foreign Subsample**
Log Private Wage	-0.949***	-0.659***	-1.790***	-2.491***	-1.959***	-3.836***
	(0.195)	(0.251)	(0.318)	(0.529)	(0.681)	(0.853)
Log Private Wage*Skill Intensity				0.413***	0.352***	0.528***
				(0.095)	(0.126)	(0.147)
Log Private Wage* Demand Elasticity				-0.298***	-0.252***	-0.369***
				(0.060)	(0.079)	(0.094)
Log Agglomeration	0.323***	0.400***	0.141	0.326***	0.401***	0.147*
	(0.050)	(0.063)	(0.086)	(0.050)	(0.063)	(0.086)
Log Local Firms	1.069***	0.918***	1.319***	1.087***	0.930***	1.359***
	(0.108)	(0.138)	(0.177)	(0.109)	(0.139)	(0.178)
Log Population	1.757***	1.838***	1.583***	1.753***	1.834***	1.586***
	(0.163)	(0.215)	(0.258)	(0.163)	(0.215)	(0.258)
Skilled Labor Ratio	0.117***	0.087***	0.165***	0.118***	0.087***	0.167***
	(0.008)	(0.010)	(0.013)	(0.008)	(0.010)	(0.013)
Log Telephone Density	0.338***	0.376***	0.399**	0.325***	0.370***	0.371**
	(0.109)	(0.143)	(0.173)	(0.109)	(0.143)	(0.173)
Log Private Market Size	-2.936***	-2.687***	-3.203***	-2.965***	-2.704***	-3.271***
	(0.255)	(0.333)	(0.395)	(0.255)	(0.333)	(0.395)
Squared Log Private Market Size	0.204***	0.164***	0.270***	0.205***	0.165***	0.274***
	(0.024)	(0.032)	(0.035)	(0.024)	(0.032)	(0.035)
Change in State Ownership	-5.383***	-5.881***	-5.370***	-5.452***	-5.923***	-5.477***
	(0.823)	(1.112)	(1.251)	(0.824)	(1.113)	(1.254)
SEZ or OCC	1.344***	0.933***	1.850***	1.351***	0.937***	1.868***
	(0.139)	(0.189)	(0.210)	(0.139)	(0.189)	(0.210)
Regional Fixed Effects						
Central	1.618***	1.645***	1.359***	1.623***	1.648***	1.374***
	(0.158)	(0.194)	(0.269)	(0.158)	(0.194)	(0.269)
Coastal	1.723***	1.971***	1.230***	1.735***	1.977***	1.256***
	(0.174)	(0.223)	(0.288)	(0.174)	(0.223)	(0.288)
Northeast	0.991***	0.910***	0.906***	0.998***	0.913***	0.920***
	(0.162)	(0.208)	(0.265)	(0.162)	(0.208)	(0.265)
Northwest	0.325	0.103	0.435	0.324	0.102	0.433
	(0.213)	(0.282)	(0.340)	(0.213)	(0.282)	(0.340)
Number of Observations	80752	47908	32844	80752	47908	32844
Pseudo R^2	0.182	0.181	0.202	0.183	0.182	0.205
Log-Likelihood	-7862.422	-4666.986	-3118.752	-7848.158	-4661.208	-3109.143

Notes:

1. All covariates are lagged by one year; Gansu and Tibet are excluded.
2. "***", "**" and "*" denote significance levels at 1 percent, 5 percent and 10 percent levels, respectively.

Table 4. Models With Control Functions

	Wage Variable Without Interactions			Wage Variable With Interactions		
	Full Sample	**ECE Subsample**	**Foreign Subsample**	**Full Sample**	**ECE Subsample**	**Foreign Subsample**
Log Private Wage	-2.079***	-1.716***	-2.944***	-3.185***	-2.793***	-4.345***
	(0.462)	(0.598)	(0.653)	(0.726)	(0.915)	(1.157)
Log Private Wage*Skill Intensity				0.371***	0.356**	0.452***
				(0.106)	(0.141)	(0.165)
Log Private Wage*Demand Elasticity				-0.368***	-0.339***	-0.431***
				(0.069)	(0.091)	(0.107)
Log Agglomeration	0.459***	0.522***	0.298***	0.463***	0.525***	0.302***
	(0.075)	(0.090)	(0.114)	(0.075)	(0.087)	(0.115)
Log Local Firms	0.956***	0.827***	1.173***	0.971***	0.836***	1.208***
	(0.121)	(0.148)	(0.194)	(0.121)	(0.150)	(0.199)
Log Population	1.675***	1.798***	1.418***	1.670***	1.794***	1.422***
	(0.185)	(0.234)	(0.280)	(0.186)	(0.232)	(0.283)
Skilled Labor Ratio	0.104***	0.074***	0.150***	0.104***	0.075***	0.151***
	(0.011)	(0.013)	(0.016)	(0.011)	(0.013)	(0.016)
Log Telephone Density	0.570***	0.621***	0.572***	0.562***	0.618***	0.549***
	(0.151)	(0.205)	(0.200)	(0.152)	(0.190)	(0.208)
Log Private Market Size	-2.881***	-2.646***	-3.127***	-2.911***	-2.669***	-3.193***
	(0.268)	(0.346)	(0.409)	(0.268)	(0.345)	(0.410)
Squared Log Private Market Size	0.193***	0.152***	0.261***	0.196***	0.154***	0.266***
	(0.026)	(0.035)	(0.037)	(0.026)	(0.034)	(0.037)
Change in State Ownership	-5.908***	-6.387***	-5.853***	-5.991***	-6.437***	-5.980***
	(1.033)	(1.285)	(1.381)	(1.044)	(1.270)	(1.427)
SEZ or OCC	1.195***	0.827***	1.638***	1.197***	0.830***	1.651***
	(0.168)	(0.203)	(0.243)	(0.169)	(0.208)	(0.250)
Regional Fixed Effects						
Central	1.595***	1.632***	1.345***	1.602***	1.637***	1.362***
	(0.166)	(0.198)	(0.272)	(0.167)	(0.201)	(0.275)
Coastal	1.687***	1.920***	1.251***	1.703***	1.928***	1.286***
	(0.186)	(0.236)	(0.296)	(0.187)	(0.240)	(0.299)
Northeast	0.678***	0.616**	0.614**	0.680***	0.614**	0.630**
	(0.201)	(0.263)	(0.304)	(0.202)	(0.254)	(0.311)
Northwest	0.163	-0.037	0.257	0.162	-0.039	0.258
	(0.227)	(0.301)	(0.352)	(0.229)	(0.292)	(0.353)
Residual	1.721***	1.518**	1.914**	-1.880	-0.377	-3.055
	(0.614)	(0.763)	(0.922)	(1.669)	(2.198)	(2.722)
Residual*Skill Intensity				0.398	0.046	0.642
				(0.309)	(0.425)	(0.458)
Residual*Import Demand				0.411**	0.535**	0.358
				(0.193)	(0.258)	(0.285)
Number of Observations	80752	47908	32844	80752	47908	32844
Pseudo R^2	0.183	0.182	0.203	0.185	0.184	0.206
Log-Likelihood	-7854.583	-4663.425	-3115.200	-7832.277	-4653.435	-3102.665
CF Wald Statistic				21.91***	10.73**	11.47***
(p-value)				(0.000068)	(0.013)	(0.0094

Notes:

1. All covariates are lagged by one year; Gansu and Tibet are excluded.
2. "***", "**" and "*" denote significance levels at 1 percent, 5 percent and 10 percent levels, respectively.

Table 5. Estimated Own and Cross Wage Elasticities, by Province

Provinces	Full Sample		ECE Sample		Foreign Sample	
	Own Elasticity	Cross Elasticity	Own Elasticity	Cross Elasticity	Own Elasticity	Cross Elasticity
Anhui	-2.09	0.04	-1.71	0.02	-2.99	0.01
Beijing	-1.96	0.17	-1.67	0.06	-2.87	0.13
Fujian	-2.07	0.06	-1.70	0.04	-2.98	0.02
Guangdong	-1.86	0.27	-1.57	0.17	-2.91	0.10
Guangxi	-2.11	0.02	-1.72	0.01	-2.99	0.01
Guizhou	-2.12	0.00	-1.73	0.00	-3.00	0.00
Hainan	-2.12	0.01	-1.72	0.01	-3.00	0.00
Hebei	-2.00	0.13	-1.67	0.06	-2.93	0.08
Heilongjiang	-2.07	0.06	-1.71	0.03	-2.97	0.03
Henan	-2.08	0.05	-1.71	0.03	-2.98	0.02
Hubei	-2.06	0.07	-1.69	0.04	-2.97	0.03
Hunan	-2.08	0.05	-1.70	0.03	-2.98	0.02
Inner Mongolia	-2.12	0.01	-1.73	0.00	-2.99	0.01
Jiangsu	-1.72	0.41	-1.55	0.18	-2.74	0.26
Jiangxi	-2.10	0.03	-1.72	0.02	-2.99	0.01
Jilin	-2.09	0.04	-1.72	0.02	-2.97	0.03
Liaoning	-2.00	0.13	-1.69	0.04	-2.90	0.11
Ningxia	-2.13	0.00	-1.73	0.00	-3.00	0.00
Qinghai	-2.13	0.00	-1.73	0.00	-3.00	0.00
Shaanxi	-2.11	0.02	-1.73	0.01	-3.00	0.01
Shandong	-1.89	0.24	-1.62	0.12	-2.87	0.14
Shanghai	-2.03	0.10	-1.70	0.04	-2.94	0.07
Shanxi	-2.11	0.02	-1.73	0.01	-3.00	0.01
Sichuan	-2.11	0.02	-1.72	0.01	-2.99	0.01
Tianjin	-2.07	0.06	-1.71	0.02	-2.97	0.04
Xinjiang	-2.13	0.00	-1.73	0.00	-3.00	0.00
Yunnan	-2.13	0.00	-1.73	0.00	-3.00	0.00
Zhejiang	-2.02	0.11	-1.68	0.05	-2.94	0.06

Note: These estimates are based on the last three columns in Table 4.

Table 6. Average Estimated Own Wage Elasticity, by Industry

ISIC	Industry Name	Skill	Demand Elasticity	Full Sample	ECE Sample	Foreign Sample
324	Footwear	4.29	2.41	-1.99	-1.69	-2.70
331	Wood	4.51	1.95	-1.81	-1.52	-2.50
321	Textiles	4.63	2.64	-1.99	-1.68	-2.72
390	Other	4.80	2.27	-1.83	-1.53	-2.52
323	Leather	4.81	1.77	-1.67	-1.39	-2.35
341	Paper	5.22	3.16	-1.94	-1.64	-2.64
311	Food	5.33	3.57	-2.03	-1.72	-2.74
356	Plastic	5.41	1.69	-1.47	-1.19	-2.10
361	Pottery	5.45	1.85	-1.51	-1.23	-2.14
322	Apparel	5.53	3.16	-1.85	-1.55	-2.53
313	Beverages	5.57	2.45	-1.64	-1.35	-2.28
332	Furniture	5.75	2.53	-1.59	-1.31	-2.21
381	Fabricated Metal	5.76	3.03	-1.75	-1.45	-2.40
369	Mineral	5.81	1.80	-1.38	-1.11	-1.99
355	Rubber	5.94	2.57	-1.56	-1.28	-2.18
382	Non-electric Machinery	6.29	3.06	-1.58	-1.30	-2.19
342	Printing	6.38	3.13	-1.60	-1.31	-2.23
354	Misc Petroleum and Coal	6.41	2.51	-1.40	-1.12	-2.00
362	Glass	6.41	1.69	-1.15	-0.89	-1.71
352	Other Chemicals	6.43	5.07	-2.12	-1.80	-2.82
351	Industrial Chemicals	6.52	4.83	-2.02	-1.70	-2.70
385	Professional	6.57	1.83	-1.16	-0.89	-1.72
383	Electric Machinery	6.75	2.02	-1.15	-0.89	-1.71
384	Transport	6.96	3.26	-1.45	-1.17	-2.04
372	Non-ferrous Metals	7.38	6.64	-2.29	-1.95	-3.01
371	Iron and Steel	8.27	8.54	-2.55	-2.18	-3.29
353	Petroleum Refineries	9.88	7.16	-1.67	-1.35	-2.24
Mean		**6.04**	**3.21**	**-1.71**	**-1.42**	**-2.36**

Data sources for skill measure and demand elasticity: see Table 1.
Jiangsu Province is taken as the benchmark province in elasticity calculation; The last three columns are based on the coefficient estimates in the last three columns of Table 4; Industries are sorted by skill intensity.

Table 7. Dynamic Simulation of 10 and 25 Percent Wage Subsidies

Zone	Province	Change for 10 Percent Wage Subsidy (percent)	Change for 25 Percent Wage Subsidy (percent)
Central			
	Anhui	24.59	72.33
	Henan	30.80	81.56
	Hubei	20.28	66.80
	Hunan	25.38	73.05
	Jiangxi	19.37	64.99
	Shanxi	33.90	85.21
Coastal			
	Beijing	-8.36	-25.53
	Fujian	-14.39	-30.99
	Guangdong	-9.66	-26.46
	Hainan	-13.59	-30.23
	Hebei	-6.25	-25.38
	Jiangsu	-10.34	-27.74
	Shandong	-10.07	-28.20
	Shanghai	-7.98	-24.83
	Tianjin	-12.55	-29.24
	Zhejiang	-6.12	-24.50
Northeast			
	Heilongjiang	24.52	72.08
	Jilin	22.59	69.87
	Liaoning	24.99	72.56
Northwest			
	Inner Mongolia	24.73	73.02
	Ningxia	29.76	79.41
	Qinghai	35.87	88.38
	Shaanxi	15.31	59.44
	Xinjiang	31.84	82.29
Southwest			
	Guangxi	19.07	64.11
	Guizhou	25.81	74.39
	Sichuan	29.76	79.38
	Yunnan	32.87	83.83