Does Export Demand Elasticity Influence Foreign Investors' Wage Sensitivity? Evidence from Multinational Location Decisions in China*

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Abstract

This paper estimates the sensitivity of foreign investors to wage differences across Chinese provinces, accounting for industry variation in export market demand elasticities. With data on 2884 manufacturing equity joint venture projects in China during 1993-1996, we estimate investor sensitivity to host wages and how this sensitivity varies with demand characteristics in China's largest export market, as well as with industry factor intensity and prior foreign investment. Using a control function technique for conditional logit developed by Petrin and Train (2010), 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 most labor intensive activities exhibit the most wage sensitivity. Using the Broda-Weinstein (2006a) estimates of the elasticity of substitution across imported product varieties to measure firms' ability to shift higher costs forward, we find that investors in those industries facing the most elastic demand in the US market are the most sensitive to wages differences, controlling for the factor intensity of the activity. We also find that while OECD investors are more responsive to wage differences than are investors from Hong Kong, Taiwan and Macau, they are less likely to choose a location that has received a large share of prior foreign investment. Simulations of an increase in relative coastal-inland wages produce a substantial shift in foreign capital toward inland provinces. These inward movements, however, do not alter the average labor intensity of firms choosing these locations.

I. Introduction

Better working conditions and higher wages remain elusive for millions of workers engaged in export processing throughout the developing world. While some argue that multinational firms can afford to pay higher labor costs, others claim that manufacturers at ground zero in the global supply chain compete fiercely to earn small profit margins.[1] These small margins underlie industry claims that higher labor costs would force them to shift investment to locations where wages remain low. Recent labor unrest at Chinese factories making parts for Western companies illustrates the pressures operating in the quest for higher wages and better working conditions at export processing factories. Even as it doubled wages at its Shenzhen campus in response to harsh international attention to its labor practices, Foxconn, a Taiwanese-owned supplier to Apple, Dell, and Hewlett-Packard, repeatedly suggested that competitive conditions could necessitate moving production away from the coastal province to newer facilities in North and Central China, where wages are lower.[2]

Companies making goods as different as computers and sporting goods assert that they do not have the "pricing power" to absorb higher labor costs.[3] They argue that since competition makes it impossible to pass higher costs on to their customers, they are forced to avoid locations with relatively high wages or labor market regulation. This reasoning places export market conditions at the heart of firms' location choice behavior. If firms are price takers on international markets, any jurisdiction that experiences increased labor costs must offer a fully offsetting differential in some form or see new investment flow to lower wage locations.

Recent estimates of import demand elasticities, however, find that these elasticities are substantially less than infinite in many industries and that firms' claims of having no "pricing power" may be overstated. Indeed, Broda and Weinstein (2006a) estimate the elasticity of substitution across alternative sources of similar goods exported into the United States and find wide variation in the competitive conditions faced by firms in different industries. Dividing goods into the three Rauch (1999) categories, they find that the average elasticity of substitution is much higher for commodities than it is for reference priced goods and that the average for reference priced goods is higher than that for differentiated goods. Multinationals operating in industries that are imperfectly competitive face downward sloping demand and an exporting firm choosing a new investment location may be less sensitive to wage differences across jurisdictions if it faces a lower demand elasticity in its export markets. Smaller compensating differentials would be sufficient to induce firms to choose a high-wage location when some forward shifting of these costs to consumers is possible.

Given the importance to developing countries of attracting foreign investment while simultaneously raising labor conditions, surprisingly little is known about the response of foreign investors to wage differences across alternative locations and what role, if any, is played by export market conditions. This paper estimates the sensitivity of foreign investors to wage differences across Chinese provinces, accounting for industry variation in export market demand elasticities. In essence, we test whether the behavior of multinational firms investing in China reflects competitive conditions in export markets, in addition to other factors. We posit a model in which Chinese made goods are imperfect substitutes for similar goods produced in other countries competing in the same export market. Foreign investors engaging in export processing from China compare profits across locations, taking the behavior of other firms as given. In this monopolistically competitive framework, firms perceive some ability to pass higher wage costs in any one location on to consumers, with the extent of cost shifting determined by the elasticity of substitution across product varieties available in the same market. In industries facing relatively high substitution elasticities, the ability to pass costs forward will be limited and foreign investors in that industry will be more sensitive than others to cross-provincial variation in wages when searching for production locations within China.

To measure export market conditions, we use the Broda and Weinstein (2006a) U.S. elasticities of substitution across similar imports produced in different countries. These estimates are well suited to our purpose for several reasons. First, Broda and Weinstein estimate these elasticities using an econometric procedure derived from a model of monopolistic competition that we share and which fits the Chinese setting. In this context, the substitution elasticity determines the firm's markup over marginal cost and, thus, is an appropriate measure of market power. Secondly, the U.S. market is the largest market for foreign-invested enterprise (FIE) exports from China and, thus, American market conditions reflect important constraints on the pricing behavior of multinational firms exporting from China. Lastly, these estimates are based on literally thousands of observations and thus are quite precise.

A second feature of our analysis is our use of the control function in conditional logit analysis, as pioneered by Petrin and Train (2010), to address potential omitted variable bias identified in earlier studies. Applying this technique 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 most labor-intensive activities exhibit the most wage sensitivity. While controlling for the factor intensity of the industry, however, we find that demand conditions in export markets also influence location decisions. C*eteris paribus*, investors in those industries where demand for Chinese-made goods is most elastic are the most sensitive to wage differences. Accounting for both factor intensity and demand elasticity, highly sensitive investors include those producing iron and steel, non-ferrous metals, and chemicals. Among the least sensitive investors include those producing electrical machinery (including communication devices), professional and scientific equipment, and glass and glass products.

Because earlier literature has found evidence of significant differences in the behavior of investors from the ethnically Chinese economies (ECE) of Hong Kong, Macau, and Taiwan and the behavior of investors from other, primarily OECD, countries, we also investigate the extent to which these groups differ in their response to wages and other location characteristics. While export market conditions and factor intensity influence both types of investors, we find that 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 networks in the context of weak formal institutions.[4]

China is a suitable setting for a study of investors' responsiveness to wages. It is a large country with centralized labor market regulation. Nonetheless, due in part to limited labor mobility, there is wide geographic variation in wages. China also provides a setting in which we are able to observe variations in behavior across industries, because foreign investment flows were large and dispersed across sectors and provinces. As Huang (2003) notes, in comparison to other countries at similar stages of development, FDI inflows to China during the 1990s were remarkable for their wide distribution among industries and provinces.[5]

The next section discusses the difficulties previous project-level studies of FDI have encountered in estimating investor's wage sensitivity. These studies indicate the need to control for omitted variable bias in location choice studies and we describe the control function approach as applied to conditional logit analysis. In Section III, we follow with a model of location choice by firms engaged in export processing and we use this model as 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, emphasizing differences in wage sensitivities across industries and investor groups. To assess the magnitude implied by our estimates for the response of investors to a relative wage increase in coastal provinces, we simulate a wage subsidy program designed to shift foreign investment toward inland provinces and present the results of this analysis in Section VI. We conclude in Section VII with a discussion of how awareness of the role of export demand elasticity in firms' location decisions informs efforts to improve labor market conditions in developing countries.

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 (2005), 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 regional 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).[6] Indeed, in some specifications the estimated wage coefficient is positive. An 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 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.[7] 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).[8] 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).[9] 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.[10] A second reason why 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 (2010) based on control functions, and further developed by Kim and Petrin (2010a). 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 and Train (2010) introduce the use of control functions to the estimation of conditional logit models.

Liu, Lovely, and Ondrich (2010) apply this control function method 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. Chen and Moore (2010) also adopt a control function technique in their study of the location decisions of French multinational firms

III. The Location Choice Model

The Profit Function

A multinational firm seeks to invest one unit of capital somewhere in China.[11] The new venture will engage in processing of a differentiated good for export.[12] The multinational firm compares potential profits across locations, taking the behavior of other firms as given, and will locate production in the province that maximizes its profit.[13] The firm produces with a generalized Cobb-Douglas technology, using variable inputs of labor, imported intermediates, and a vector of locally-provided services. Log profits for a firm producing good g if it locates in province j can be written as:

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

where τ_j reflects the (perhaps concessionary) tax rate on foreign investment in province j, p_{gc} is the price on world markets of 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 Chinese exports of good g.

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 (2006a).[14] Global demand for Chinese varieties of good g, which depends on 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 country of origin.[15] The elasticity of substitution among varieties of good *g* is assumed to exceed unity: $\sigma_g > 1$.

Whichever location it chooses, the firm will set its product 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 potential 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 intermediates, p_m, a price index for locally-provided inputs, p_s:

$$\ln c_{gj} = \theta_{gl} \ln w_j + \theta_{gm} \ln p_{mj} + \theta_{gs} \ln p_{sj}, \tag{4}$$

where θ_{gk} $(k = l, m, s)$ denotes a cost share in industry *g*. Using (3) and (4), we obtain an expression for variable profits that is decreasing in local factor prices and tax rate:

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

It is clear from (5) that the effect on potential variable profits of a higher provincial wage, *ceteris paribus*: (i) is larger for firms in industries with a larger labor cost share, θ_{gl}; and (ii) is larger for firms in industries facing a higher elasticity of substitution in export markets, σ_g.

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, N_j^f, and the number of domestic firms who may undertake the costly upgrading necessary to serve foreign firms, $\bar{N}_j^s$. Assuming log-linear functional forms, this framework allows us to derive an intermediates price index for locally-provided service inputs:

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

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

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

Adding an error vector e to capture firm-province idiosyncratic cost shocks, 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

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

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.[16] Regional fixed effects are added to the list of regressors to capture regional correlation in supply and demand shocks.

We use information on the location choices of multinational firms investing in China to estimate the sensitivity of foreign investors to wage differences. As suggested by the variable profit function (5), we expect this response to vary by export-market demand elasticity and factor intensity. To test for varying parameters, we interact the provincial wage with these two characteristics of the activity in which the Chinese-based venture is engaged. The first industry characteristic we interact with the provincial wage is the elasticity of substitution across imported product varieties, estimated by Broda and Weinstein (2006a) using U.S. import data for 3-digit industries over the period 1990-2001.[17] We expect that investors in an industry facing relatively high demand elasticity in export markets will be less able to shift wage costs onto consumers and, thus, will be more sensitive to provincial wage variation.

The second industry characteristic we interact with wage is a measure of factor intensity based on the average wage paid by the industry in China. Data on average wages by industry is drawn from the 1995 Third Industrial Census, a complete census of formal economic activity in China. Correlation of the average wage with estimates of the 1995 capital-labor ratio is 0.71. The average wage, however, reflects human capital intensity as well as a premium for physical capital intensity and thus is a better indicator of the share of production costs that goes to hourly wage workers. A direct measure of human-capital intensity, science and technology expenditures as a share of value added in 1995, is available from Chinese firm-level data.[18] We prefer the average wage to this alternative because the former is based on the Economic Census rather than a relatively small sample of firms and, thus, is measured with less error than the science and technology share. 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 than are firms with large unskilled labor shares.

Finally, to permit responsiveness to vary by source, we estimate conditional logits using three samples: the full sample, projects funded from ECE sources of Hong Kong, Macau, and Taiwan and projects funded from other, primarily OECD, sources. [19] Previous work suggests that investors from Hong Kong, Macau, and Taiwan are less responsive to wage differences (Fung, Iizaka, and Siu 2003; Fung, Iizaka, Lin, and Siu 2005), a finding that may reflect technology differences or strong attachment to specific locations. Technological differences between ECE and OECD investors are consistent with the findings of Dean, Lovely, and Wang (2009), who find that ECE investors are deterred by pollution taxes while OECD investors are not. Other researchers, such as Wang (2001), emphasize the importance of local connections for the profitability of joint ventures in China, suggesting that ECE investors may be less sensitive to factor price differences across province as they choose investment locations based on geographic or personal proximity. For these reasons, we investigate the extent to which these two types of investors differ in their response to wages.

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:[20]

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

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.

Kim and Petrin (2010a, b) 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.

Using this method, 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) in province *j* is used as Z_j. Liu, Lovely and Ondrich provide justification for the assumption that private-sector wages are influenced by provincial characteristics that drive multi-factor productivity, while SOE wages are not. We 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.[21]

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).[22] The sample contains EJVs undertaken during 1993-1996 using project descriptions available from the Chinese Ministry of Foreign Trade and Economic Cooperation (MOFTEC).[23] Provinces are grouped into five regions: coastal, northeast, central, southwest, and northwest.[24] 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.

After China reformed its foreign investment regime in 1992, the entry of foreign-invested enterprises (FIEs) fueled rapid export growth.[25] During the following five years of stable and liberal policy toward FDI, these enterprises contributed 32% of fixed asset investment by all non-state firms and accounted for more than half of Chinese manufactured exports.[26] As reported by Huang (2003), working with data from the 1995 Chinese Industrial Census, foreign enterprises were dominant in export sales in a wide variety of industries, accounting for more than 50 percent of all exports in garments and footwear, leather, sporting goods, electronics and communications, food processing, wood products, paper products, printing and record pressing, rubber products, plastic products, metal products and instruments.[27]

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 private provincial 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 in each province, which we use as a first-stage instrument.[28] 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. 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 $(\overline{N}_S)$ is measured by the number of domestic firms, defined as the total number of domestic enterprises at the township level and above (thereby capturing larger enterprises that may have the capacity to supply a foreign-invested plant).

To control for potential local 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

We begin by estimating the wage sensitivity of all investors, ECE investors alone, and OECD investors alone. Our results support the use of the control function to address endogeneity concerns. They also indicate that ECE and OECD investors place different weights on the wage and other provincial characteristics when choosing an investment location. After discussion of these benchmark results, we re-estimate the model, allowing wage sensitivity for each group to vary with industry characteristics.

Sensitivity by Investor Group: Benchmark and Control Function Results

Table 3 reports the results of conditional logit estimation, for the full sample, the ECE subsample and the OECD 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 inclusion of the control function. 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). Looking first at results using the full sample, the wage coefficient is negative and precisely estimated. All covariates have the expected signs and all are highly significant even in the presence of regional fixed effects.[29] 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.

As shown in the second and third models of Table 3, which omit the control function, the probability of an ECE or an OECD 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 OECD 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 OECD sample appears to be more deterred from investing in provinces with relatively high wages. OECD investors' lack of family and business ties to specific provinces may allow these investors to be more sensitive to differences in production costs when choosing a location. 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.[30]

Observed clustering by ECE investors may also reflect a heavy weight placed by them on proximity to related investments and to the source country. Evidence consistent with either 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 (highly significant) but about a third of that magnitude, 0.141, for OECD investors (insignificant at 10% level). ECE investors are somewhat more likely than OECD investors to locate in the central and coastal provinces and less likely to locate in the northwest. 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, all consistent with the view that these investors have access to networks and local connections perhaps not accessed by OECD investors.

Models (4), (5), and (6) in Table 3 provides results estimated with the inclusion of the control function as well as regional fixed effects for the full sample and both subsamples. 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.

Comparing the benchmark results to those obtained when a control function is added, the estimated coefficients for the residual from the first-stage wage regression is positive and significant at the 1 percent level for the full sample and each subsample. Kim and Petrin (2010b) 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. Inferences from other estimated coefficients are unchanged by the addition of the control function.

Estimation using a control function provides evidence of a great sensitivity to wages for both subsamples of investors. The estimated coefficient for ECE investors increases from -0.66 to -1.72 when the control function is added, while for OECD investors it increases from -1.79 to -2.94. Significant differences in the behavior of these groups continue to be evident. Indeed, the elasticity of the probability of locating in a given province with respect to a unit decrease in its log wage is 72% higher for OECD investors than for ECE investors. OECD investors are less sensitive to prior foreign investment (the probability of locating in a given province with respect to a one unit increase in log agglomeration is 43% less for this group than for ECE investors) but more sensitive to the presence of local firms who may be potential local suppliers (their elasticity is 42% higher). In sum, the control function provide evidence of substantial downward bias in the benchmark estimates and a highly elastic response to wages by all investors.

These findings differ from inferences drawn from econometric analyses of regional FDI inflows that distinguish investors by source. Fung, Iizaka, Lin, and Siu (2005), who estimate a random effects model using regional data from 1990-1999, find that Hong Kong investment flows are more sensitive to local labor costs than are flows from the United States. The authors ascribe the observed difference in behavior to clustering by US-owned firms in capital intensive sectors and to the export processing focus of Hong Kong owned enterprises. Fung, Iizaka, and Siu (2003) compare Japanese and Hong Kong flows into Chinese regions and also find that Hong

Kong investment is more sensitive to way differences. Our results, based on project-level data and conditional logit analysis, do not support this characterization of differences in behavior. Rather, our findings suggest that OECD investors weight local wages more heavily than do ECE investors, at least at the time that the host province is chosen. We now turn to additional analysis that allows for differences along industrial characteristics, including factor intensity.

Allowing for Differences by Export Market Conditions and Factor Intensity

To investigate how wage sensitivity is conditioned by industry characteristics, we interact the provincial wage with measures of factor intensity and export market conditions. Based on our previous findings supporting its use, we estimate these conditional logits using a control function approach. Results are shown in Table 4.

Because previous research suggests that differences among investors in wage sensitivity may be explained by differences in the factor intensity of their projects, we proceed by first introducing an interaction of the provincial wage with a measure of capital intensity of the activity, expecting a less elastic response from investors whose Chinese ventures are more capital intensive. The first three models of Table 4 provide no support for the contention that attraction to low wages is a function of factor intensity. The interaction of log provincial wage and industry capital intensity is positive but not significantly significant, for the full sample and for each subsample.[31] Other inferences are not affected by the inclusion of the interaction term.

Because these models include interactions involving the wage, we form the control function by including interactions between the first-stage residual and the industrial characteristic. As seen in Table 4, some, but not all, control functions terms are individually significant. Testing whether the 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 5 percent level in all three samples. These results reinforce the indication of omitted variable bias present in the models that omit the control function.

To explore the hypothesis that export market conditions influences firms' wage sensitivity, we also interact the provincial wage with a measure of demand elasticity, the Broda-Weinstein (2006a) elasticities of substitution estimated for the U.S. import market.[32] These demand elasticities are shown in Table 5 for each industry. There is a positive correlation between the capital intensity measure and the Broda-Weinstein import demand elasticity – more capital intensive industries face more elastic market conditions, in part because these industries tend to produce homogeneous commodities. Because high capital intensity is predicted to reduce wage sensitivity while elastic market demand raises it, by not accounting explicitly for demand elasticity, we may incorrectly infer that factor intensity does not matter for wage sensitivity. This explains why we obtain insignificant coefficients for the capital intensity and wage interaction term in the first three columns of Table 4.

Following our theoretical model, we expect the coefficient on an interaction of the wage and the import elasticity to be negative—higher price elasticity reduces the ability to shift higher wage costs to consumers and makes investors more sensitive to provincial wage variation. We control for both factor intensity and demand elasticity simultaneously. As shown in the last three columns of Table 4, the wage and both wage interaction terms have the expected signs and are highly significant for all three samples. Higher demand elasticity is associated with a greater aversion to high wage provinces: for the full sample, the estimated coefficient on the interaction of wage and import demand elasticity is -0.368 and highly significant. This result is consistent with the hypothesis that firms facing more competitive conditions in export markets are less able to absorb higher wages by passing them to customers. We also find that more capital intensive industries are less sensitive to the wage: for the full sample, the estimated coefficient on the wage-factor intensity interaction is 0.371 and highly significant, as expected.

When the sample is split into investor groups, as shown in the fifth and sixth models, capital intensity reduces wage sensitivity for both groups, but more so for OECD investors. Export demand conditions are significant influences on wage sensitivity for both groups but the estimated coefficient for the OECD sample is larger than it is for the ECE sample, -0.431 versus -0.339. 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.

Accounting for these differential responses widens the gap between ECE and OECD responses: the estimated wage coefficient for OECD investors in the footwear industry is -2.46, compared to an estimate of -1.06 for ECE investors. Again, these estimates are precisely estimated. At the mean capital intensity and mean U.S. import substitution elasticity, the wage coefficient for OECD investors is -2.01, while for ECE investors it is -0.76. Differences between the two groups widen as the capital intensity of the industry rises. For example, the wage coefficient for the most capital-intensive activity (petroleum refining) is more than four times larger for OECD investors (-1.26) than for ECE investors (-0.29).

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 OECD samples, as shown in Table 5, using estimated coefficients from Table 4. Comparing the last two columns, we see that the OECD elasticity is larger than the ECE elasticity for every industry, but both subsamples produce a similar ranking across industries. Some interesting comparisons across industries emerge when we look at these rankings. In the mid 1990s, industries with 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.[33] 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. Certainly, local labor forces are subject to different wage pressures, depending on the natural advantages of the local area.

Wage Elasticities, By Province

Table 6 provides estimated own and cross wage elasticities, by province, calculated using the estimates in Table 4. 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. Looking across locations, the own-wage elasticity is smallest for those provinces with the highest predicted probability of being chosen, including Beijing, Guangdong, Jiangsu, and Shandong. 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 own wages rise (due to lower own elasticities in coastal provinces) or when inland provinces lower their wages (due to very low cross elasticities of inland provinces). However, our estimates also imply that these coastal provinces have the largest effect on other province's chances of attracting investment if they do attempt to keep wages low.

VI. Simulation of a Higher Relative Coastal Wage

Is the response to higher relative coastal wages the inland movement of labor intensive industries? We use our estimated coefficients to simulate the effect of an increase in the relative wage by assuming the central government offers a wage subsidy for inland provinces. This simulation gauges the potential for policy or market induced shifts in investment location. 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 changes in relative regional wage levels.

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 percent, for each province. When we increase the intervention to a 25 percent wage subsidy, however, coastal FDI shrinks between 17 percent and 18 percent. Thus, relative wages shifts do appear to be effective in shifting investment away from these more prosperous areas.

For the inland provinces, changes in relative labor costs can raise the FDI stock substantially, starting from a relatively low base. For the Central region, a 10 percent wage subsidy increases the stock of foreign investment by 16 to 17 percent and a 25 percent wage subsidy increases foreign investment by 47 to 48 percent. These impacts are similar for other inland regions and indicate that relative wage shifts 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. Before-and-after distributions of inflows across regions are shown in Figure 2, where we see that despite inward shifts, coastal clustering remains.

Relative wage changes also affect the industrial composition of regional foreign capital flows, as suggested by the variation in own wage elasticities shown in Table 5. We calculate the change in the average capital intensity and the average import demand elasticity of investors choosing each province. We find that the average capital intensity rises while the average demand elasticity falls for projects that continue to locate in the coastal region. At the same time, the average capital intensity of inland investments falls while the average demand elasticity rises. Surprisingly, though, given the relatively large location shifts we observe in the simulation, these changes in the character of investment are very small, with neither industrial characteristic changing more than 3 percent on average. The small average effect can be attributed to the positive correlation between capital intensity and demand elasticity, especially for homogenous commodities. From these simulations we conclude that an increase in relative coastal-inland wages shifts foreign capital toward inland provinces, but it does not alter the average labor intensity of firms choosing these locations.

VII. Conclusion

In general, observed location choices reflect complex calculations by firms faced with 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 connections to particular regions. ECE investors, in contrast to OECD investors, are less sensitive overall to wages in the host province. They also place greater weight on previous investment, much of it from ECE sources. For both groups, responsiveness depends on the capital intensity of the venture. These results direct our attention to the role comparative advantage plays in labor market conditions and they suggest that wage pressures on local hosts change as relative factor endowment shift during the development process.

The Economist magazine recently highlighted the role of factor intensity in speculation on the response by foreign investors to higher coastal wages in China, arguing that relative wage shifts would induce inward movement of labor intensive factories (*The Economist*, Economic Focus, June 12, 2010, p. 86). Our estimates provide strong support for the view that factor intensity matters for wage sensitivity, but we do not find that the most labor intensive industries are the most responsive to regional wage shifts. We show that in addition to factor intensity, demand conditions in export markets influence how investors involved in export processing respond to wages, and that investors producing homogenous commodities are among the most sensitive. These findings enrich our understanding of multinational firm behavior by identifying the previously unexamined influence of export market conditions on FDI location choice.

In developing countries, 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. Export processing FDI also integrates the host country more deeply into world markets. The response of these markets to increases in labor costs, as may result from enforcement of minimum wages or maximum work hours, shape the policy space available to local communities seeking better wages and working conditions. Even the perception that labor market regulation will deter foreign investors may lead to weak enforcement by governments and muffled calls for reform from labor organizers. Such a chain of responses fuels fears of a "race to the bottom" in labor standards.[34]

Progress in measuring the response of international investment flows to rising wages in China and other locations is important in addressing these fears. We see separate roles for industrial factor intensity and host country endowments, on the one hand, and export market demand elasticity, on the other. Explicit acknowledgment of market conditions can also inform analyses of policies that seek to improve labor conditions by altering consumer demand, such as "fair trade" labeling, or final-goods producers' sourcing patterns, such as "no sweatshop" campaigns.[35] At a minimum, a focus on export market conditions helps identify those industries in which such efforts may be useful. Given the large flows of direct investment predicted in the wake of the recent global recession, additional research on the links between developed country export markets and developing country labor markets seems warranted.

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 (2010) 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.[36] 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.[37] 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 ECE firms and for OECD firms, both with and without a wage subsidy to inland provinces. Letting n stand for the source category of the firm, we have $n = \mathrm{C}$ or $n = \mathrm{O}$. 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:

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

where

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

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 other 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 . A prominent example of such calls for higher wages and better conditions is the *New York Times* editorial of July 6, 2010, entitled “China, the Sweatshop.” Analysts perceptions of export processing firms ability to cope with higher costs are reported in “Supply Chain for iPhone Highlights Costs in China,” *The New York Times*, July 5, 2010, http://www.nytimes.com/2010/07/06/technology/06iphone.html?pagewanted=1&sq=Foxconn%20Technology&st=cse&scp=2.

2 . These wage increases followed suicides at two campuses in Southern China owned by Foxconn Technologies. These suicides were widely seen as the spark for unrest at other export-processing factories in China. Foxconn’s consideration of inland location for production facilities is reported in “Supply Chain for iPhone Highlights Costs in China,” The New York Times, July 5, 2010.

3 . See “Supply Chain for iPhone Highlights Costs in China,” The New York Times, July 5, 2010.

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

5 . In the 1995 Industrial Census, no industry received more than 10% of total FDI. The geographic distribution of foreign investment within China is highly uneven, as it is in most host countries. Henley et al. (1999) report that 80% of cumulative FDI inflows is located in one of China’s ten eastern provinces. However, while interior regions received only 13% of cumulative FDI from 1992 to 1998, that exceeded all FDI inflows to India during the same period.

6. A recent exception to this pattern is Amiti and Javorcik (2008), who use a different technique. They relate changes in the number of foreign-invested firms in Chinese provinces to changes in the average wage.

7. Petrin and Train (2010) provide examples from studies of differentiated product models, including the well-known study by Berry, Levinsohn, and Pakes (1995).

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

9. 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.

10. 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.

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. In 1995, FIEs export sales accounted for about 40% of total FIE sales (Huang 2003, Table 1.4), with wide variation by industry and source. This share is an underestimate of the importance of foreign markets to FIE sales because it does not include sales of goods that are further processed within China and then re-exported.

13. 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.

14. 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.

15. As in Romer (1994), Rutherford and Tarr (2002) and Broda and Weinstein (2006a), variety is defined by country of origin. 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).

16. 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.

17. US import elasticity estimates were downloaded from files made available at http://faculty.chicagobooth.edu/christian.broda/website/research/unrestricted/TradeElasticities/TradeElasticities.html.

18. 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. The correlation between this skill measure and the average wage is 0.43.

19. Grouping of projects into ECE and other 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. Other foreign partners are those from other sources, primarily OECD countries, with the largest shares from the US and Japan. There is no source for 12% of projects in 1996, 17% in 1995, 10% in 1994, and 3% in

1993. Since most FDI inflows at this time were ECE, these projects were designated ECE. Because Malaysia, Indonesia, and the Philippines have large ethnically Chinese populations, the few projects from these countries are also included in the ECE subsample. Our results are not sensitive to either inclusion.

20. This discussion adapts the discussion of consumers' choice among differentiated products in Petrin and Train (2010) to the location choice context.

21 . 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."

22. More recent samples of new foreign investment projects, distinguished by location, industry and source country, do not exist. Amiti and Javorcik (2008) examine the role of trade costs in the location of foreign firms, using data from 1998-2001. Their data are drawn from the Annual Survey of Industrial Firms, collected by China's National Bureau of Statistics, for firms with sales above 5 million RMB. They estimate the number of new foreign firms entering each year by comparing year-to-year foreign firm counts. While this approach has some advantages, including broad coverage, it misses new entrants with sales below the cut-off level, it treats firms moving above scale as new entrants, and it cannot distinguish inflows from net flows.

23. 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.

24. 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.

25. In 1992 China removed many sectoral and regional FDI restrictions (Lardy 1994).

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

27. See sales and export shares by industry in Huang (2003), Table 1.4, page 24.

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

29. While we expect that a larger local market will attract foreign investors producing for local consumption, in the presence of regional fixed effects we do not have strong priors for the coefficients for private market size and its square. Estimates suggest a U-shaped relation between private market size and the probability of its being chosen.

30. Huang (2003, p. 40, n 67) documents the greater clustering of ECE-funded ventures, which are less evenly distributed across provinces than is investment from Japan and the United States. Expectations of favors based on local business connections of ECE investors are supported by extensive interviews summarized in Wang (2001).

31. One may wonder if the inclusion of the control function leads to the insignificant interaction term. Unreported estimates, performed without inclusion of the control function, produce coefficients for the wage-capital intensity interaction that are significant at the 10% level for the full and OECD samples only. These estimates are available from the authors upon request.

32. In unreported regressions, we substituted the Broda-Greenfield- Weinstein (2006b) estimates of China's import demand elasticity for the U.S. elasticity of substitution. These results indicate no significant relationship between the wage sensitivity of foreign investors and Chinese domestic market conditions. Given that on average foreign invested enterprises export more than half of their output, this result is not surprising.

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

34 . The case for a "race to the bottom" in labor standards, is developed by Chan (2003).

35 . Harrison and Scorse (2010) find that anti-sweatshop activity targeted at specific final-goods producers led to large wage gains and limited job losses at Indonesian contract manufacturers in the textile, footwear, and apparel sectors.

36. 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.

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

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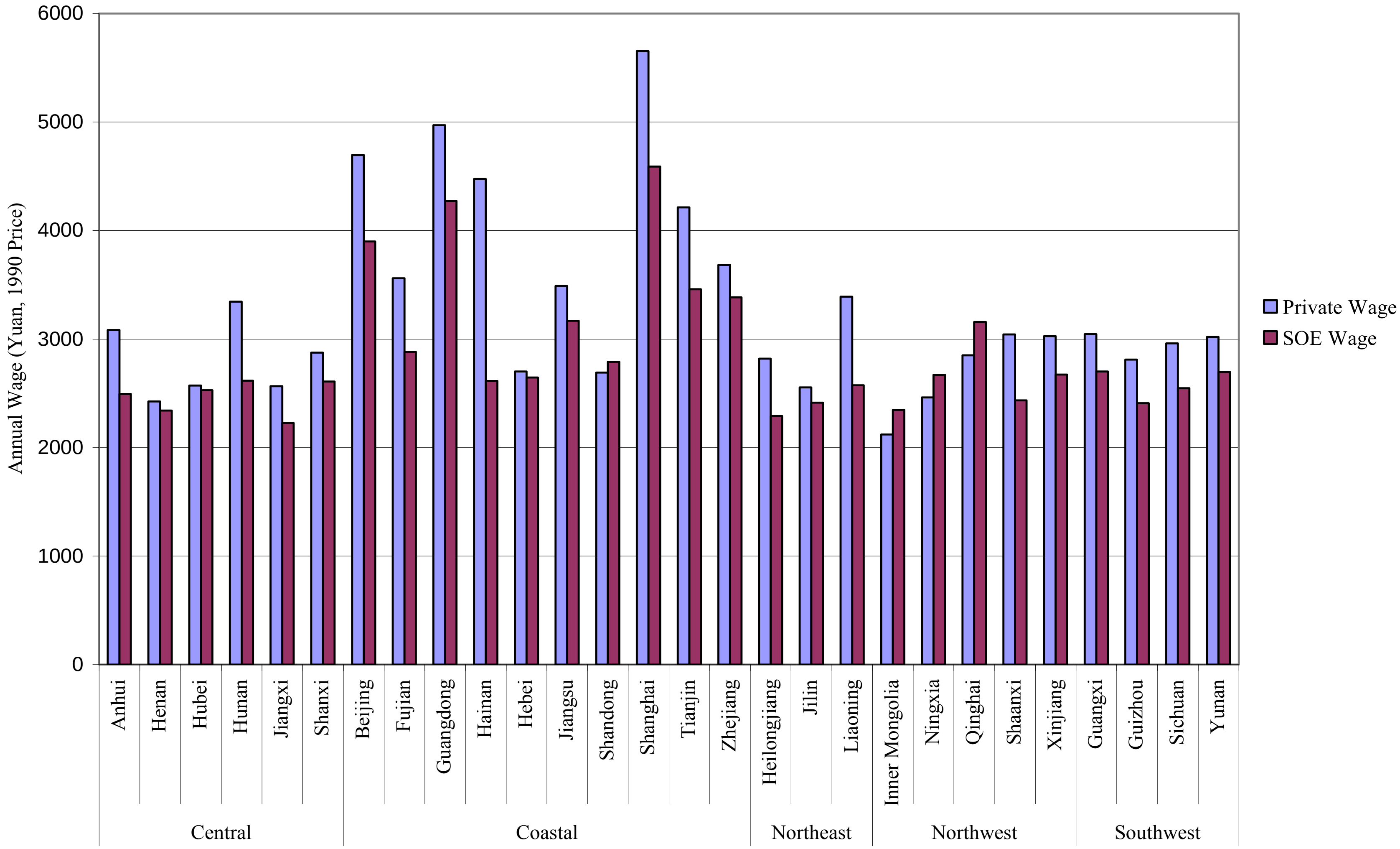
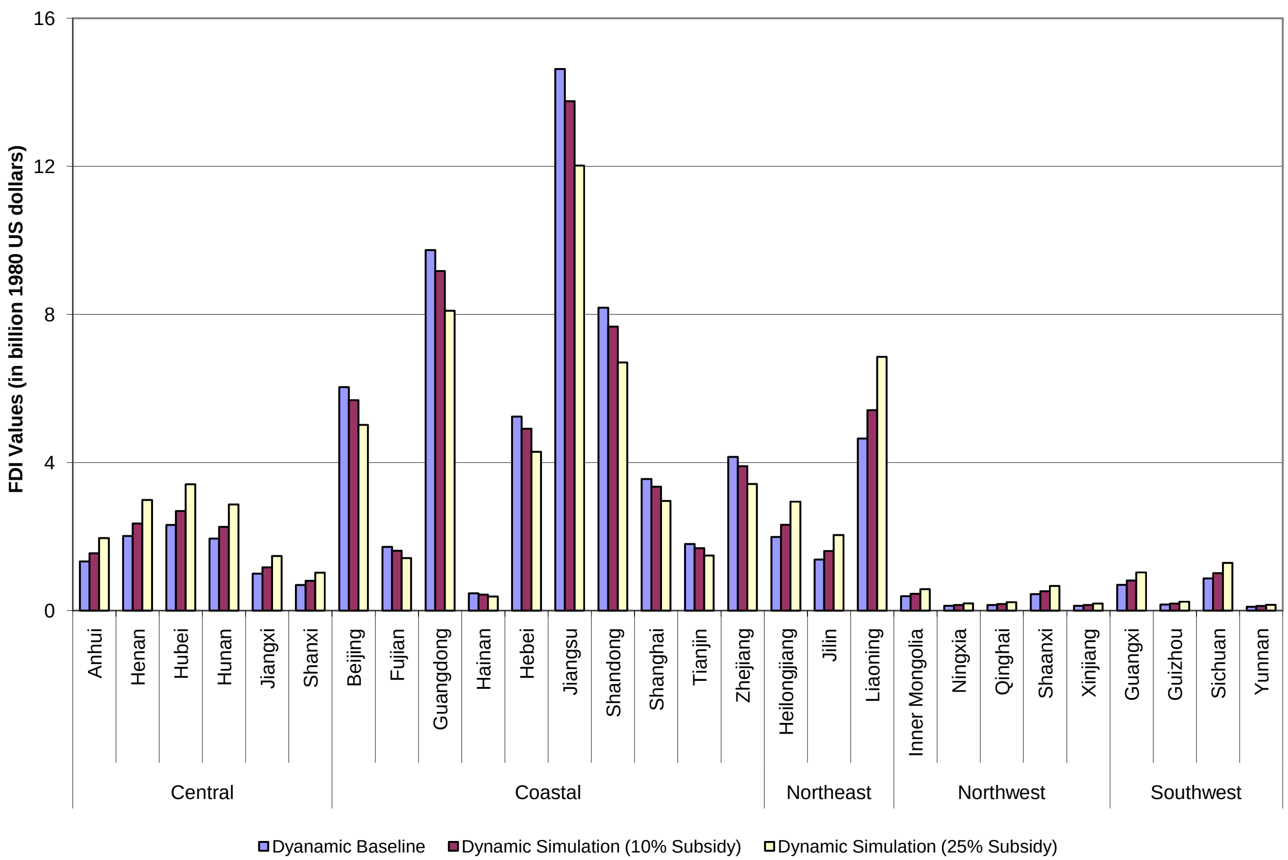
Figure 1: Average private wage and average SOE wage, by province, 1992-1995



Source: See Table 1.

Figure 2: Comparing baseline FDI to dynamically simulated FDI with 10% and 25% wage subsidy to inland regions



Source: Based on simulations by authors.

Table 1. Data Definitions and Sources

Variable	Definition	Source	Mean*
EJV project:			
Location	Province	*Almanac of China's Foreign Economic Relations*	
Source	ECE=Macao, Taiwan, Hong Kong, other South Asian countries	*and Trade,* various years,	
	OECD=all other countries	Dean, Lovely and Wang (2009)	
Industry	3-digit ISIC Rev.2 classification		
SOE Wage	Average annual wage for industrial workers in state-owned enterprises, in 1990 yuan, by province	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, by province	Branstetter and Feenstra (2002), from *China Statistical Yearbook*, various years	3254
Capital 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
U.S. Elasticity of Substitution	U.S. elasticity of substitution across import varieties, estimated using 1990-2001 data, concorded by authors from SITC Rev. 3 to ISIC Rev.2 classification	Broda and Weinstein (2006a)	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, by province	*China Statistical Yearbook*, various years, Dean, Lovely and Wang (2009)	16061
Population	Population, in millions, by province	*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), by province	*China Statistical Yearbook*, various years and calculations by authors	12.08
Telephone Density	Number of urban telephone subscribers per million persons, by province	*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, by province	*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
Yunnan	3021	113	7000	39	5	11000	0.73	16
Zhejiang	3684	1251	36000	43	9	32000	0.19	127

Table 3. Multinomial Logit Estimates of Location Choice, by Model and Sample

	Without Control Functions			With Control Functions		
	Full Sample	**ECE Subsample**	**OECD Subsample**	**Full Sample**	**ECE Subsample**	**OECD Subsample**
Log Private Wage	-0.949***	-0.659***	-1.790***	-2.079***	-1.716***	-2.944***
	(0.195)	(0.251)	(0.318)	(0.462)	(0.598)	(0.653)
Log Agglomeration	0.323***	0.400***	0.141	0.459***	0.522***	0.298***
	(0.050)	(0.063)	(0.086)	(0.075)	(0.090)	(0.114)
Log Local Firms	1.069***	0.918***	1.319***	0.956***	0.827***	1.173***
	(0.108)	(0.138)	(0.177)	(0.121)	(0.148)	(0.194)
Log Population	1.757***	1.838***	1.583***	1.675***	1.798***	1.418***
	(0.163)	(0.215)	(0.258)	(0.185)	(0.234)	(0.280)
Skilled Labor Ratio	0.117***	0.087***	0.165***	0.104***	0.074***	0.150***
	(0.008)	(0.010)	(0.013)	(0.011)	(0.013)	(0.016)
Log Telephone Density	0.338***	0.376***	0.399**	0.570***	0.621***	0.572***
	(0.109)	(0.143)	(0.173)	(0.151)	(0.205)	(0.200)
Log Private Market Size	-2.936***	-2.687***	-3.203***	-2.881***	-2.646***	-3.127***
	(0.255)	(0.333)	(0.395)	(0.268)	(0.346)	(0.409)
Squared Log Private Market Size	0.204***	0.164***	0.270***	0.193***	0.152***	0.261***
	(0.024)	(0.032)	(0.035)	(0.026)	(0.035)	(0.037)
Change in State Ownership	-5.383***	-5.881***	-5.370***	-5.908***	-6.387***	-5.853***
	(0.823)	(1.112)	(1.251)	(1.033)	(1.285)	(1.381)
SEZ or OCC	1.344***	0.933***	1.850***	1.195***	0.827***	1.638***
	(0.139)	(0.189)	(0.210)	(0.168)	(0.203)	(0.243)
Regional Fixed Effects						
Central	1.618***	1.645***	1.359***	1.595***	1.632***	1.345***
	(0.158)	(0.194)	(0.269)	(0.166)	(0.198)	(0.272)
Coastal	1.723***	1.971***	1.230***	1.687***	1.920***	1.251***
	(0.174)	(0.223)	(0.288)	(0.186)	(0.236)	(0.296)
Northeast	0.991***	0.910***	0.906***	0.678***	0.616**	0.614**
	(0.162)	(0.208)	(0.265)	(0.201)	(0.263)	(0.304)
Northwest	0.325	0.103	0.435	0.163	-0.037	0.257
	(0.213)	(0.282)	(0.340)	(0.227)	(0.301)	(0.352)
Residual				1.721***	1.518**	1.914**
				(0.614)	(0.763)	(0.922)
Number of Observations	80752	47908	32844	80752	47908	32844
Pseudo R^2	0.182	0.181	0.202	0.183	0.182	0.203
Log-Likelihood	-7862.422	-4666.986	-3118.752	-7854.583	-4663.425	-3115.200

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. Allowing Wage Sensitivity to Vary with Factor Intensity and US Substitution Elasticity, by Model and Sample

	With Control Functions			With Control Functions		
	Full Sample	**ECE Subsample**	**OECD Subsample**	**Full Sample**	**ECE Subsample**	**OECD Subsample**
Log Private Wage	-2.451***	-1.942**	-3.772***	-3.185***	-2.793***	-4.345***
	(0.720)	(0.880)	(1.114)	(0.726)	(0.915)	(1.157)
Log Private Wage*Capital Intensity	0.060	0.037	0.133	0.371***	0.356**	0.452***
	(0.090)	(0.114)	(0.143)	(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***	0.299***	0.463***	0.525***	0.302***
	(0.075)	(0.088)	(0.115)	(0.075)	(0.087)	(0.115)
Log Local Firms	0.952***	0.824***	1.170***	0.971***	0.836***	1.208***
	(0.122)	(0.147)	(0.195)	(0.121)	(0.150)	(0.199)
Log Population	1.676***	1.799***	1.423***	1.670***	1.794***	1.422***
	(0.193)	(0.228)	(0.280)	(0.186)	(0.232)	(0.283)
Skilled Labor Ratio	0.103***	0.074***	0.149***	0.104***	0.075***	0.151***
	(0.011)	(0.013)	(0.016)	(0.011)	(0.013)	(0.016)
Log Telephone Density	0.578***	0.626***	0.585***	0.562***	0.618***	0.549***
	(0.159)	(0.197)	(0.202)	(0.152)	(0.190)	(0.208)
Log Private Market Size	-2.876***	-2.644***	-3.129***	-2.911***	-2.669***	-3.193***
	(0.273)	(0.343)	(0.412)	(0.268)	(0.345)	(0.410)
Squared Log Private Market Size	0.193***	0.152***	0.261***	0.196***	0.154***	0.266***
	(0.027)	(0.034)	(0.037)	(0.026)	(0.034)	(0.037)
Change in State Ownership	-5.915***	-6.383***	-5.906***	-5.991***	-6.437***	-5.980***
	(1.066)	(1.271)	(1.396)	(1.044)	(1.270)	(1.427)
SEZ or OCC	1.190***	0.824***	1.633***	1.197***	0.830***	1.651***
	(0.170)	(0.201)	(0.243)	(0.169)	(0.208)	(0.250)
Regional Fixed Effects						
Central	1.591***	1.630***	1.341***	1.602***	1.637***	1.362***
	(0.167)	(0.199)	(0.272)	(0.167)	(0.201)	(0.275)
Coastal	1.689***	1.920***	1.256***	1.703***	1.928***	1.286***
	(0.190)	(0.233)	(0.297)	(0.187)	(0.240)	(0.299)
Northeast	0.673***	0.613**	0.606**	0.680***	0.614**	0.630**
	(0.207)	(0.256)	(0.306)	(0.202)	(0.254)	(0.311)
Northwest	0.162	-0.037	0.252	0.162	-0.039	0.258
	(0.232)	(0.297)	(0.353)	(0.229)	(0.292)	(0.353)
Residual	-2.839*	-1.848	-3.718	-1.880	-0.377	-3.055
	(1.634)	(2.057)	(2.672)	(1.669)	(2.198)	(2.722)
Residual*Capital Intensity	0.768***	0.572*	0.937**	0.398	0.046	0.642
	(0.251)	(0.334)	(0.401)	(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	0.183	0.204	0.185	0.184	0.206
Log-Likelihood	-7847.471	-4661.122	-3110.259	-7832.277	-4653.435	-3102.665
CF Wald Statistic	16.93***	6.97**	10.61**	21.91***	10.73**	11.47***
(p-value)	(0.00021)	(0.0307)	(0.00497)	(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. Average Estimated Own Wage Elasticity, by Industry

ISIC	Industry Name	Capital Intensity	Demand Elasticity	Full Sample	ECE Sample	OECD 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 capital intensity 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 capital intensity.

Table 6. Estimated Own and Cross Wage Elasticities, by Province

Provinces	Full Sample		ECE Sample		OECD 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: Elasticities based on the coefficient estimates in the last three columns of Table 4.

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	0.16	0.48
	Henan	0.17	0.48
	Hubei	0.16	0.48
	Hunan	0.16	0.47
	Jiangxi	0.16	0.48
	Shanxi	0.16	0.47
Coastal			
	Beijing	-0.06	-0.17
	Fujian	-0.06	-0.18
	Guangdong	-0.06	-0.17
	Hainan	-0.06	-0.17
	Hebei	-0.06	-0.18
	Jiangsu	-0.06	-0.18
	Shandong	-0.06	-0.18
	Shanghai	-0.06	-0.17
	Tianjin	-0.06	-0.17
	Zhejiang	-0.06	-0.18
Northeast			
	Heilongjiang	0.17	0.48
	Jilin	0.16	0.48
	Liaoning	0.16	0.47
Northwest			
	Inner Mongolia	0.17	0.48
	Ningxia	0.16	0.48
	Qinghai	0.16	0.48
	Shaanxi	0.16	0.48
	Xinjiang	0.17	0.48
Southwest			
	Guangxi	0.16	0.47
	Guizhou	0.17	0.48
	Sichuan	0.17	0.48
	Yunnan	0.16	0.48

Note: Based on the coefficient estimates in the fourth column of Table 4.