Examining Determinants of Foreign Wage Premiums in China

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Abstract

We estimate foreign ownership wage premiums for every 3-digit manufacturing industry in China and discover a wide range of premiums both for so-called "foreign" ownership and for overseas Chinese ownership of firms. Foreign ownership generates larger and more prevalent wage premiums than overseas Chinese ownership of firms, but both types of foreign ownership produce wage premiums that respond similarly in hypothesis testing of determinants. Using the number of computers per worker as an indicator of a firm's technology level, we find support in 76-78% of industries for the hypothesis that foreign firms pay higher wages to reduce the risk of worker turnover and the accompanying technology leakage to domestic rivals. However, this determinant explains only 5-6% of the foreign wage premium, on average. We find the most intensive support for the "fair wage" hypothesis that foreign firms pay higher wages because they are more profitable than domestic firms and workers in more profitable firms expect to be paid more, otherwise they will shirk. This hypothesis explains an average of 8-9% of the foreign wage premiums, with support for the hypothesis found in 72-75% of the industries using firm's total profits per worker as the added wage determinant. Intangible assets and training costs were found to be much weaker individual determinants of foreign wage premiums. When we consider the best combination of explanatory variables to include in each industry's wage regression, we find support for our combined hypotheses in the vast majority of industries, but we still find large residual wage premiums attached to foreign ownership in China.

Keywords: FDI, foreign ownership, wages, China

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1. Introduction

The empirical literature documenting wage premiums paid by foreign-invested enterprises relative to domestic enterprises is extensive and so are the accompanying hypotheses on why these wage premiums exist. What are much more limited, however, are tests of these hypotheses. Of the many reasons why foreign firms might pay more than domestic firms, which have empirical support and which do not? With worldwide foreign direct investment (FDI) inflows totaling over $1 trillion every year since 2006, it is vital for policymakers to understand fully the various host country effects of FDI, including labor market effects.[1] In this paper, we begin to address this gap in the literature by testing two hypotheses to explain foreign-ownership wage premiums using firm-level data for China.

Lipsey and Sjoholm (2004) suggest four possible hypotheses to explain foreign ownership wage premiums: 1) host-country requirements or pressures; 2) workers' preferences for working for a domestic, rather than foreign, employer; 3) foreign firms' disadvantage relative to domestic firms in identifying high-quality workers without paying wage premiums; and 4) foreign firms' stronger aversion to worker turnover due to higher training costs or fear of technology leakage to domestic rivals. The last of these hypotheses is the most amenable to quantitative testing with firm-level data, so we chose that one to pursue. This hypothesis is based on efficiency wage models.[2] Firms will pay above market-clearing wages to reduce worker turnover, and their willingness to pay higher wages increases with the costs of replacing workers. If worker turnover is more costly for foreign firms than for domestic firms, foreign firms should pay higher wages. Another variation of the efficiency wage concept involves the

[1] Another line of inquiry examines FDI impacts on host countries through technology transfers and spillovers. See Damijan, Rojec, Majcen, and Knell (2013) for a recent summary of this literature.
[2] See Yellen (1984) for a summary of these models, and Krueger and Summers (1988) for supportive empirical evidence.

"fair wage" hypothesis developed in Akerlof and Yellen (1990). Workers at more productive and profitable firms expect to be paid more, otherwise they shirk. This hypothesis helps to explain the foreign wage premium if foreign firms are more profitable than their domestic counterparts. We are also able to test this hypothesis using firm-level data from China.

Lipsey and Sjoholm (2004) were among the first to confirm that foreign ownership wage premiums exist even after controlling for region, industry, plant size and worker characteristics. They found a 12% wage premium paid by foreign firms to blue-collar workers and a 22% wage premium paid to white-collar workers in Indonesian factories. Aitken, Harrison and Lipsey (1996) find substantial foreign wage residuals for Mexico and Venezuela as host countries, but not for the U.S. as a host country, when they control for plant size, location, type of industry and skill mix. Some studies have gone further in trying to control for differences in worker characteristics by using matching employer-employee data. Martins (2011) uses matching data from Portugal to show that some of the pay differential between foreign and domestic firms is explained by the foreign firms' tendency to hire more able workers. Heyman, Sjoholm and Tingvall (2007) use matching data from Sweden to conclude that foreign firms' higher wages mostly can be explained by firm and worker characteristics.

Egger and Kreickemeier (2011) argue that differences in observable firm-level characteristics such as capital-intensity and worker quality provide only partial explanations of the foreign wage premium. They develop a heterogeneous firms model in which firm-specific and country-specific factors interact to explain the foreign wage premium. If firms in more developed economies have higher productivities on average, then foreign investment by these firms into less developed economies produces one source of a wage premium (i.e., more productive firms pay more). Another source of a wage premium is generated by multinational firms that earn "global profits" and share them with their workers worldwide. In a less developed economy, domestic firms with identical productivities to foreign-invested firms from a more developed economy can coexist but the foreign firms will pay higher wages due to their larger global profits. Our testing of the fair wage hypothesis relates only indirectly to the Egger and Kreickemeier (2011) model because we are not able to observe the global profits of the foreign firms in our dataset. Instead, we examine whether foreign firms pay higher wages due to their higher profits earned in China.

Greaney and Li (2013) document a wide range of foreign wage premiums that exist in China even when they focus on a single industrial region, the Yangtze River Delta, to examine pay differences across manufacturing firms in the same 2-digit industry. After controlling for firms' exporter status, location, sub-sector, capital-intensity, size, workforce education and gender, they find foreign ownership wage premiums of 36% and 15% in the General Equipment and Textiles Industries, respectively. That research also finds overseas-Chinese-ownership wage premiums of 18% and 12% for the two industries, respectively. In the current paper, using an efficiency wages perspective, we seek to understand why foreign ownership generates such different wage premiums in different industries in China.

We contribute to the literature by estimating foreign wage premiums for each 3-digit manufacturing industry in China, while controlling for the standard set of observable firm and workforce characteristics (i.e., firm capital-intensity, size, workforce education and gender, location, and industry sub-sector), plus exporter status.[3] We are among the first to estimate foreign wage premiums while controlling for exporter status, which should tend to reduce our foreign wage premiums relative to other estimates since foreign firms are more export-oriented

[3] Exporter status is added due to the results found in Greaney and Li (2013).

than domestic firms and exporter wage premiums are widely acknowledged as a stylized fact.[4] Even after controlling for all of these firm-level differences, we find a wide range of foreign ownership wage premiums across the manufacturing industries. We use the cross-industry variation in wage premiums to look for commonalities across industries that generate high or low foreign wage premiums and we conduct hypothesis testing on the determinants of the foreign wage premiums. To our knowledge, our research is the first to systematically examine the determinants of foreign wage premiums.

We tally our results along both extensive and intensive margins using the numbers of industries providing supportive evidence of our hypotheses for the former, and quantifying the strength of our supportive evidence for the latter. Using firm-level data from China, we are able to compare wage premiums across two groups of foreign owners—so-called “foreigners” versus overseas Chinese owners from Hong Kong, Macao or Taiwan. Although we find differences between these two foreign ownership types in the magnitudes and prevalence of wage premia across industries, we find that both types of foreign ownership produce wage premia that respond similarly in hypothesis testing of determinants. Next we provide a description of our data, followed by a discussion of our hypothesis testing methodology, and then our results and conclusions.

2. Data

We use firm-level data from the Financial Information Database for Chinese industrial enterprises provided by the National Bureau of Statistics of China (NBSC). The database covers all industrial firms in China in 2004 with sales of 5 million yuan or more. After data cleaning,

[4] See Bernard and Jensen (1995, 1997) and Schank, Schnabel and Wagner (2007).

we have 265,466 firms in our dataset.[5] These firms can be divided into 39 industries at the 2-digit level, including 30 manufacturing industries, 6 mining industries and 3 utilities and recycling industries. We focus on the manufacturing industries, which include 246,696 firms, and further disaggregate these firms into 168 3-digit industries.

As described in detail in Greaney and Li (2013), the firms in our dataset are classified by ownership into five types: state-owned enterprises (SOEs), collectives, private domestic enterprises (PDEs), foreign-direct-invested enterprises (FDIEs) and Hong-Kong-Macao-Taiwan-invested-enterprises (HMTEs). Joint-venture firms are classified according to their largest shareholder's firm type to reflect the managerial control of the firm.[6] We estimate wage premiums for FDIEs and HMTEs separately to allow for country-specific ownership effects that might lead to differing wage premiums and determinants thereof. Huang (2004) finds that HMTEs and FDIEs have different technology spillover effects, and Greaney and Li (2012) find evidence suggestive of differing impacts on China's labor market. Potential advantages that HMTEs may have over FDIEs in China include having closer language and cultural linkages, closer geographic proximity, and greater ease in obtaining visas and other government approvals.

Our dataset provides firm-level employment numbers for each skill (i.e., education level) and gender group, but not separate wage data for each, only total wages per firm. These wage totals are used along with employment totals to calculate average annual wages per worker for each firm. The strength of our data is the detailed information we have at the firm level to use in explaining the variation in average wages across firms in the same industry. A weakness of our

[5] The data is cleaned by excluding firms that report less than 10 employees or less than 2,000 yuan in total output or total assets, or report values that include apparent errors (i.e., negative values for assets, exports exceeding total sales, sum of employment subgroups exceeding total reported, etc.). We lose about 4% of firms in our chosen industries through data cleaning.

[6] As documented in Greaney and Li (2013), joint-ventures (JVs) are predominantly foreign-invested firms with minority domestic partners, mainly PDEs. Less than 1% of domestic firm types are JVs, but 44% of HMTEs and 51% of FDIEs are JVs.

data is that we do not have wages by skill level of workers at each firm. An additional weakness of the NBSC data is that the workforce education statistics are reported only for 2004, not for other years, so we are limited to a cross-sectional approach.

3. Methodology

We estimate a foreign wage premium for FDIEs and for HMTEs relative to PDEs for each 3-digit industry in China, then use these estimates to conduct hypothesis testing on the determinants of the foreign wage premia. Our wage regression follows Lipsey and Sjoholm (2004), but we make modifications to accommodate a broader set of firm types and to control separately for the influence of exporter status on wages. In our benchmark regressions, we estimate the determinants of firm-level wages using robust regression for the following equation:[7]

(1) $\ln w_i = \alpha + \sum \beta_m Control_i^m + \sum \gamma_n FirmType_i^n + \delta_1 Exporter_i + \delta_2 PureExporter_i + \sum \theta_j City_{ij} + \sum \mu_k Sector_{ik} + \varepsilon_i.$

Our level of analysis is at the 3-digit industry level, so w_i represents average annual wage per worker for firm i in a single 3-digit industry in China. $Control_i$ represents m control variables for firm i that are expected to influence its wages, $FirmType_i$ represents n ownership dummy variables for firm i, $Exporter_i$ represents an exporter dummy variable for regular exporters ($0 <$ export share of sales ≤ 0.9), and $PureExporter_i$ is a dummy variable for pure exporters (export share of sales > 0.9). $City_{ij}$ is a dummy variable equal to one if firm i is located in city j, and zero otherwise;[8] and $Sector_{ik}$ is an industry dummy equal to one if firm i is in 4-digit industry k, and equal to zero otherwise. The control variables include the capital-labor ratio (i.e., fixed assets per

[7] We use robust regression rather than ordinary least squares, as used in Lipsey and Sjoholm (2004), to limit the influence of outliers in our data.
[8] We use 287 city dummies to control for regional wage differentials. These cities include 4 municipalities, 27 province capitals and 256 prefectural cities. A prefectural level city ranks below a province and above a county in China's administrative structure.

worker) to control for differing levels of capital-intensity across firms, total employment to control for firm size (i.e., scale economies effects), the weighted average of workers' education years to control for labor quality differences across firms,[9] and the share of female workers in the firm's workforce to account for gender wage differentials.[10] The expected sign on the first three control variables is positive, and on the last variable is negative due to the gender wage gap.[11]

The firm type variables are expressed as dummy variables identifying the legal ownership classification for the firm—SOE, Collective, HMTE or FDIE. A significant coefficient for any of these specified firm types indicates a difference for that firm type relative to the average PDE, which make up the majority of firms in our dataset.

The inclusion of Exporter and PureExporter dummy variables is prompted by Defever and Riaño (2012) who find that China's preferential subsidies offered to pure exporters prompts an odd clustering of firms that export almost all of their output, which is not typically observed in other countries.[12] They also find that pure exporters tend to be less productive than regular exporters but more productive than non-exporters. We want to identify the firm-type wage premia separate from any exporter-type wage premia, so that hypotheses regarding the determinants of each can be separately examined.

Each wage regression at the 3-digit industry level has a large number of potential independent variables since we have 4 control variables, 4 firm types, and 2 exporter types, plus varying numbers of city and sector dummy variables. To increase our confidence in our

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[9] The weighted average of workers' education years is calculated as follows: $edu_i = (19*L_i^{graduate} + 16*L_i^{college} + 15*L_i^{associate} + 12*L_i^{high} + 9*L_i^{middle})/TL_i$ where TL_i is the total number of workers in firm i, $L_i^{graduate}$, $L_i^{college}$, $L_i^{associate}$, L_i^{high}, and L_i^{middle} are number of workers with highest education at graduate, 4-year college, 3-year college, high school or middle school and below levels in firm i, respectively.

[10] The control variables are centered around the mean values for PDE firms in each 3-digit industry.

[11] Su and Heshmati (2011) find that women earned only 82.5% of what men earned on average in China in 2011, and they conclude that 85% of the gender wage gap is due to gender discrimination not worker characteristics.

[12] One exception is the observation of pure exporters in Vietnam, as described by McMillan and Woodruff (1999).

estimated coefficients, we set a minimum industry size of 200 firms for inclusion in our wage regressions. Of the 168 manufacturing industries at the 3-digit level, we drop 19 that fall below this sample size criterion, resulting in 149 industries with 244,397 firms for our analysis.

Our first step in analyzing the foreign wage premia (WP) across the 149 industries is to use the WP for descriptive analysis.[13] We rank the industries by their FDIE, HMTE and SOE WP to see if the industries at the top share common characteristics that distinguish them from industries at the bottom and to compare the rankings for foreign WP versus state-owned WP. More formally, we examine correlation coefficients between the characteristics of the mean-value firm in each industry and the firm-type WP. Then we proceed to more formal hypothesis testing of two hypotheses on the sources of the foreign WP.

We test hypotheses derived from efficiency wage models. The first hypothesis links labor productivity to firm wages through managers' fears of costly worker turnover, as follows:

Hypothesis 1 (Worker Turnover Aversion Hypothesis): Due to higher training costs and/or higher fear of technology leakage to domestic rivals, foreign-owned firms have a stronger aversion to worker turnover and therefore pay higher wages than domestic rivals.

To test this hypothesis, we use three different variables to measure a firm's training costs and/or technology level: training costs per worker, intangible assets per worker, and number of computers per worker.[14] Firms are asked to report a total for intangible assets based on the value of their patent rights, non-patent technology, trademarks, copyrights, land-use rights and franchise licenses. Since firms may report zeroes for training costs, intangible assets, or computers, these added variables have true zero-value observations. To keep the information embedded in zero-value observations, we add 0.0001 to these variables before taking the

[13] We use WP throughout the remainder of the paper to represent wage premia or wage premium.

[14] Another indicator of a firm's technology level might be its research and development (R&D) expenditures, but our data set does not include this variable.

logarithm. We use a two-part test of the hypothesis: (i) do foreign firms on average have higher training costs and/or higher technology relative to domestic rivals; and (ii) does this differential partially explain the foreign firm wage premium? Each question is posed at the 3-digit industry level, with further details provided after introducing our second hypothesis.

The second hypothesis derived from efficiency wage models is the so-called "fair wage" hypothesis of Akerlof and Yellen (1990). Applied to a market with foreign and domestic firms, this hypothesis can be stated as follows:

Hypothesis 2 (Fair Wage Hypothesis): Workers at more productive and profitable firms expect to be paid more, otherwise they will shirk. Foreign firms pay more than domestic firms because they are more profitable.

To test this hypothesis, we use firm-level total profits per worker and operating profits[15] per worker in a two-part hypothesis test: (i) do foreign firms on average make higher profits than domestic firms; and (ii) does this differential partially explain the foreign WP? Again, we add 0.0001 to total profit and operating profit before taking the logarithm to keep zero-value observations in the regressions. However, negative values of total profit or operating profit are treated as missing after taking the logarithm.[16] Since we lose about 22% of our almost 250,000 firm observations by dropping those with negative total profits or operating profits reported, we establish two more sets of benchmark regression results to use in making comparisons when either profit variable is involved.[17]

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[15] A firm's operating profit equals its total profit minus profit from non-manufacturing activities, such as financial investments, appreciation of asset value, etc.

[16] In order to keep the information embedded in observations with negative profit, we also tried to transform the profit variable, either total profit or operating profit, to (profit - minimum profit + 0.0001). However, in this case, the estimated coefficients for profit became insignificant for most industries. This may be because the fair wage hypothesis only applies in cases where profits are positive.

[17] The technology and profit variables are centered using the PDE mean values in the respective 3-digit industry.

A potential problem with our profit variables is that corporate tax rules mandate that foreign firms report their profits based on their operations in China, while domestic firms must report their profits based on their operations in China and abroad.[18] However, we believe that this data discrepancy is relatively small because only a tiny share of Chinese manufacturing firms had operations abroad in 2004.[19] Also, Chinese workers' fair wage expectations might be based primarily on their firms' China operations' profitability, which they presumably know more about than their firms' outside-China profitability, so one way to compare "apples to apples" in terms of profits is to focus on firms' China-operations-only profits. However, Egger and Kreickemeier (2011) theorize that one reason why foreign ownership is good for workers in developing countries like China is that these foreign firms share their *global* profits with their developing country workers. Since we do not observe the global profits of the FDIEs or HMTEs with our data, we might be underestimating the relationship between profits and wages for foreign firms operating in China.

To test each hypothesis, we first answer question (i) using descriptive statistics for each 3-digit industry. Since the variance of some of our variables is high and outliers are observed, we use both the per-firm-mean and per-firm-median observation to compare foreign firm types to PDEs within each industry.[20] We also use the 75th percentile observation after discovering that the median value for some variables for some firm types is zero, indicating skewed distributions for those variables.

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[18] According to The Provisional Regulation of the People's Republic of China on Enterprises Income Tax effective from 1994 to 2007 for domestic firms and the Law of the People's Republic of China on Income Tax of Enterprises with Foreign Investment and Foreign Enterprises effective from 1992 to 2007 for FDIEs and HMTEs.

[19] According to the 2004 *Statistical Bulletin of China's Outward Foreign Direct Investment* published by China's Ministry of Commerce, there were only 5,163 Chinese firms invested abroad in 2004 and only 59% of these firms were in manufacturing industries. Therefore, there were only about 3,046 Chinese firms in manufacturing industries that could have earned profits abroad in 2004. This is only about 1.2% of our observations used for estimation.

[20] Since the foreign wage premiums are defined relative to PDEs, our hypotheses testing uses the same reference group.

To answer question (ii) for both hypotheses, we repeat the intra-industry wage regressions in equation (1), but this time add in the variables named above to address each hypothesis. We first look for significant and positive coefficients on these added variables as indicators that these variables are indeed positive determinants of firm-level wages. Then we look to see how the inclusion of each new wage determinant affects the estimated WP for foreign firms within each 3-digit industry. Using the wage regression results for each industry, we ask whether the inclusion of the added variable:

- (A) improved the fit of the regression (i.e., does the adjusted-R^2 value increase?);
- (B) caused the estimated foreign WP to become insignificant (i.e., when it had been significant in the benchmark case); and/or
- (C) caused the estimated foreign WP to become smaller but still significant.

To answer question (ii) in the affirmative, we look for cases that satisfy both (A) and (B), or both (A) and (C). By design, criteria (B) and (C) only apply to industries that generate a significant foreign WP in the benchmark regression. We also look for cases that appear to directly refute question (ii) by tallying cases where the added variable causes the estimated foreign WP to become larger, rather than smaller, while remaining significant. We call these cases (Z). Cases that satisfy (A) and (Z) are interpreted as evidence against our hypotheses.

We also use the results from the modified wage regressions to quantify how much of the foreign WP can be explained by each determinant individually and in combination with each other. We test for correlations between our determinants (i.e., per worker training costs, intangible assets, numbers of computers, total profits and operating profits) and find strong correlations only between total profits and operating profits (0.95), so those two variables are not included simultaneously into the wage regression. We also check for correlations between our determinants and our variables of interest (i.e., the firm-type dummy variables) and do not find strong correlations. The strongest of these correlations is between numbers of computers per worker and the FDIE dummy at 0.24.

4. Results

Table 1 summarizes the key results of our benchmark wage regression in equation (1) for 149 3-digit manufacturing industries in China.[21] The table shows the WP for different firm types, after controlling for firm capital-intensity, size, workforce education and gender, location, sub-sector, and exporter status. It also shows the WP for different exporter statuses after controlling for the control variables, location, sub-sector, and firm type. As seen in the table, the foreign firm types—FDIEs and HMTEs—generate significant, positive coefficients in most industries and these coefficients are larger, on average, than those associated with the two specified domestic firm types—SOEs and Collectives. FDIEs produce significant and positive WP over PDEs in 137 out of 149 industries, or 92% of industries, and HMTEs produce significant and positive WP in 93 industries or 62% of industries. In comparison SOEs produce significant and positive WP in only 47 industries or 32% of industries and Collectives produce significant, positive WP in only 7 industries, or 5% of industries. Collectives produce significant and negative WP relative to PDEs in 16 industries, and SOEs do the same in 12 industries, while the foreign firm types only produce a significant, negative WP in one industry for FDIEs.

The estimated WP for the same firm type are quite different across industries and the ranges are quite large: FDIE (-23.5% to 209.1%), HMTE (5.5% to 101.7%), SOE (-65.7% to 54.0%) and Collectives (-29.8% to 27.0%). Due to the large variance in estimated coefficients, we focus on the median estimated WP, rather than the mean, and find that the median WP are

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[21] Additional results from these benchmark wage regressions are summarized in Table A-1, and summary statistics on annual wages by industry appear in Table A-2.

28.4% for FDIEs, 16.8% for HMTEs, 15.2% for SOEs and -7.5% for Collectives, all relative to PDEs.[22] To directly compare the FDIE and HMTE WP within each industry, we note that 92 of the 93 industries with a significant HMTE WP also report a significant FDIE WP, and 82 of those industries have the FDIE WP larger than the HMTE WP.

We also find that the industry distributions of WP are different across different firm types. Table 2 shows the Top 10 and Bottom 10 industries ranked by firm type WP for FDIEs, HMTEs and SOEs relative to PDEs. Industries that appear more than once in the rankings are highlighted to show the common entries. In some cases, industries that appear more than once switch from being a top 10 industry to being a bottom 10 industry depending on which WP is involved. For example, industry 363 (Food, beverage, and feed manufacturing equipment) appears as a top 10 industry for FDIE and HMTE WP with 55.3% and 34.3% WP over PDEs, but also appears as a bottom 10 industry for SOE WP, at -25.8%. Industry 322 (Steel smelting) appears as a bottom 10 industry for FDIE WP, with the only negative estimated value at -23.5%, but it appears as a top 10 industry for SOE and HMTE WP, with SOEs estimated to pay 46.3% more than PDEs and HMTEs estimated to pay 50.1% more than PDEs. These two extreme examples of SOE WP may be explained by the Chinese government's continuous support of SOEs in the steel industry,[23] versus its encouragement of further privatization and openness in food processing industries.[24] Industry 332 (Noble metals processing) generates the largest FDIE WP at 209.1% and the second largest HMTE WP at 61.9%. Industry 133 (Vegetable oil processing) also appears on both foreign firms' top 10 lists, at 58.4% for FDIEs and 32.3% for

[22] For WP by exporter status, the medians are only 9.9% for Exporters and 4.4% for Pure Exporters, relative to non-exporters.
[23] In July 2005, the National Development and Reform Commission of China issued a formal policy on steel that sought to spur consolidation by increasing the concentration of steel production among large SOEs.
[24] To improve the modernization of the rural economy, the food processing industry is listed in both the 11th (for 2006-2010) and 12th (for 2011-2015) five-year development plans of the Chinese government as an important industry that needs further openness.

HMTEs. Among the bottom 10 lists, FDIEs and HMTEs do not share any common industries, but each shares a common industry with the bottom 10 list for SOEs. Industry 244 (Toys) produces only an 8.8% WP for FDIEs, while it produces a -65.7% WP for SOEs, the lowest estimated coefficient for SOEs. Industry 313 (Bricks, tiles, stones for construction) produces the lowest WP for HMTEs at 5.5%, while it produces a -9.9% WP for SOEs.

In comparing the top half of Table 2 to the bottom half to find common trends across top 10 industries that set them apart from bottom 10 industries, it is surprisingly difficult to make any general statements. Examining each top 10 group or bottom 10 group of industries by their code numbers, we can see at least three, and in some cases, all four of the 1-digit manufacturing sectors represented within each grouping. This simple observation suggests quite a wide diversity of industries can generate high or low firm-type WP. Our next step is to quantify any cross-industry commonalities by generating correlation coefficients between the significant estimated WP and the firm-level means for various statistics for those industries. This can help us to address questions such as "Do higher technology industries tend to generate higher FDIE wage premia?" Table 3 shows the results of this correlation exercise.

In Table 3, we highlight correlations that are greater than 0.4 or less than -0.4, of which there are only 5 cases. FDIE WP tend to be higher in industries that have higher average total profits or operating profits per worker, with correlations of 0.42 and 0.43. FDIE WP show the strongest correlation with our profit variables, although the other firm type WP also show positive correlations with the profit variables, ranging from 0.19 to 0.30. HMTE WP show the strongest correlation detected, at 0.46, with firm age, implying that industries with older firms on average produce larger HMTE WP. The HMTE WP also tends to increase with the average allowance paid per worker in an industry. SOE WP show no strong correlations with any of our industry averages, but the WP for Collectives show a positive correlation with the training costs per worker at 0.41.

A noteworthy result from Table 3 is that all of the firm-type WP are negatively correlated with both export variables. This means that industries that are more export-oriented on both the extensive margin (i.e., export probability) and the intensive margin (i.e., export share of sales) tend to generate smaller firm type WP. This result might be due to the presence of the exporter and pure exporter dummies in our wage regression, which may account for more wage variation in industries that are more export oriented. Also of note from Table 3 is the lack of strong correlations between the foreign WP and our technology indicators. The correlations between FDIE and HMTE WP and industries' intangible assets per worker are positive but low at 0.13 and 0.20, while the correlations between these WP and industries' numbers of computers per worker are negative but very small, at -0.01 and -0.03. It does not appear that an industry's average technology level can serve as a good predictor of the size of its foreign wage premiums. Overall in looking at Table 3, we do not get a strong set of correlations between the average firm in each industry and the foreign firms' WP in that industry.

Our next table presents a summary of our hypothesis testing results for question (i) for both hypotheses. Do foreign firms have higher training costs, higher technology levels and/or higher profits relative to PDEs, on average? We ask this question for each 3-digit industry using mean, median and 75th percentile values by firm type and then tally the affirmative responses as shown in Table 4. The table shows that for per worker training costs, only 82 industries (or 55% of industries) report a per-firm mean value for FDIEs that exceeds the per-firm mean value for PDEs. Only 30 industries show FDIEs spending more on training costs using the median firm observation within each firm type to make the comparison, and 59 show FDIEs spending more on training costs at the 75^{th} percentile level. One reason for the large disparity between the hypothesis testing using the mean versus the median values for training cost is that in 27 industries, the median value of training costs per worker is zero for all firm types. Over half of all of the firms in our dataset report zero training costs per worker. Examining the second section of Table 4, we see even smaller numbers of industries that satisfy the hypothesis that HMTEs spend more on training costs than PDEs. Overall we find that we reject the notion that foreign firms tend to spend more than PDEs on worker training in about half of the industries for FDIEs and in the vast majority of industries for HMTEs.

Table 4 shows more affirmative results for hypothesis testing using intangible assets per worker. FDIEs report higher intangible assets per worker than PDEs in 110 industries, and HMTEs do the same in 91 industries. Using median values, the numbers of industries that satisfy the criteria are lower for both foreign firm types, at 93 for FDIEs and 48 for HMTEs. At the 75^{th} percentile, both types of foreign firms report higher intangible assets in most industries, with 131 for FDIEs and 123 for HMTEs. As we found with training costs, intangible assets have a skewed distribution, with over half of the total number of firms reporting zero.

The results of hypothesis testing using numbers of computers per worker as a proxy of a firm's technology level show more affirmative results than the previously considered variables. A total of 134 industries satisfy the criteria that FDIEs have more computers per worker than PDEs using per firm means for comparison, while 118 industries satisfy the same criteria for HMTEs. The number of industries grows even further using median values, to 137 for FDIEs and 132 for HMTEs. Of our three training and technology measures, computers per worker provides the most consistent support to answer question (i) in the affirmative for the most industries, while training costs per worker failed our test the most often across industries.

Table 4 also provides summary statistics for question (i) for Hypothesis 2 regarding the link between profits and firm type. FDIEs on average make more total profit per worker than PDEs in 69-71% of industries, depending on whether we use means or medians for comparison, and more operating profit per worker in 68-72% of industries. HMTEs do not perform quite as well, earning more total profit per worker on average in only 42-46% of industries, and more operating profits per worker in 38-50% of industries. As with the training and technology variables, FDIEs tend to satisfy the profitability criterion in more industries than do HMTEs.

Table 5 presents results that address question (ii) for both hypotheses. The first column repeats information from Table 1, the initial benchmark regressions, for the sake of comparison. Columns (2)-(4) summarize our wage regression results after adding the three training and technology determinants one-by-one to the wage regression to see to what extent each of these variables can help to explain the foreign wage premium in each industry. When we add training costs per worker, it produces a significant and positive coefficient in 129 out of 149 industries, it never produces a significant and negative coefficient, and it improves the fit of our wage regression in 124 industries (i.e., satisfying criterion (A)). Therefore, we confirm that firms that spend more on worker training tend to pay higher wages in the vast majority of industries. However, differentials in worker training costs do not seem to help to explain the foreign WP in most industries. The table shows that we find no industries that satisfy criterion (A) and (B) and only 22 industries that satisfy (A) and (C) for the FDIE WP. For the HMTE WP, the numbers of industries that satisfy our criteria are even smaller. Only 1 industry satisfies (A) and (B), and 9 industries satisfy (A) and (C).

The number of cases that appear to refute question (ii) is larger at 94 industries for the FDIE WP and 72 industries for the HMTE WP. For these industries, adding training costs improves the fit of the wage regression while causing the FDIE or HMTE coefficient to increase, rather than decrease. Overall, we see that for training costs our hypothesis is refuted in 68% of industries for the FDIE WP and in 77% of industries for the HMTE WP, while it is supported in only 16% and 11% of industries respectively. These results are not surprising since we saw in Table 4 that foreign firms do not tend to spend more on worker training than PDEs in most industries. Controlling for training costs, therefore, actually tends to increase rather than decrease the size of our foreign WP in most industries reporting a foreign WP.

Our hypothesis testing results using intangible assets are somewhat more mixed, as shown in column (3). The variable itself is a significant and positive wage determinant in only 32 industries, while it is a significant and negative determinant in 4 industries. However, its inclusion improves the fit of our wage regression in 66 industries. For the FDIE WP, adding intangible assets to the wage regressions produces results that satisfy our (A) and (B) criteria in 1 industry and satisfy our (A) and (C) criteria in 39 industries. The corresponding numbers for HMTE WP are 1 and 22. These numbers are higher than for training costs, in part due to the higher numbers of industries where foreign firms tend to report higher intangible assets than PDEs, as shown in Table 4. Table 5 also shows lower numbers of industries that refute question (ii) by satisfying criteria (A) and (Z), with 23 industries for the FDIE coefficient and 19 industries for the HMTE coefficient. The bottom line results for intangible assets show support for our hypothesis in 29% of industries for the FDIE WP and 25% of industries for the HMTE WP, while contradictory evidence is found in 17% and 20% of industries respectively.

Table 5 clearly shows that adding the number of computers per worker to our wage regression performs the best out of our added training and technology variables in terms of satisfying our criteria for question (ii). In 2 industries adding the number of computers improved the regression fit and caused the FDIE coefficient to lose significance (i.e., satisfied (A) and (B)). In 106 more industries, adding the number of computers improved the regression fit and caused the FDIE coefficient to shrink, while remaining significant (i.e., satisfied (A) and (C)). The corresponding numbers for the HMTE WP are 2 and 69 industries. We find only 8 industries for the FDIE WP and 9 industries for the HMTE WP that appear to refute our hypothesis by showing a significant increase in the foreign WP after adding the number of computers per worker to the wage regression. These numbers imply support for our hypothesis in 76-78% of industries versus contradictory evidence in only 6-10% of industries.

To add per worker total profits or operating profits to our wage regressions, we need two new sets of benchmark results to reflect the loss of observations due to negative reported profit values, as described previously. These new benchmark results are summarized in column (5) for all firms with non-negative total profits and in column (7) for firms with non-negative operating profits. Adding total profits per worker as a wage determinant causes the FDIE coefficient to lose significance in 1 industry and to decrease in size in 92 other industries while also satisfying criterion (A), as shown in column (6). For the HMTE coefficient, 4 industries satisfy criteria (A) and (B) while 64 satisfy criteria (A) and (C). The results shown in column (8) using operating profits per worker instead of total profits per worker are similar in magnitude to those shown in column (6). Overall, we find support for the fair wage hypothesis in 72-75% of industries for FDIE WP and in a similar 76-77% of industries for HMTE WP. Evidence contrary to the fair wage hypothesis is found in 12-13% of industries for the FDIE WP and 9-13% of industries for the HMTE WP.

In column (9) of Table 5, we show the tallied results from using the "best-fit" wage regression for each industry. In 147 out of 149 industries we have a better fit for our wage regression using the non-negative profit restrictions reflected in results shown in columns (5) and (7) rather than the unrestricted benchmark results shown in column (1). For that reason, we use the benchmarks in columns (5) and (7) as our starting point, then sequentially add total (or operating) profit, then number of computers, then intangible assets or training costs, and then all four added variables and compare the fit of the wage regression to select the "best fit" regression (i.e., the reporting the highest adjusted R-squared value). These results allow for variation across industries in wage determinants. We find support for our combined hypotheses[25] in 80% of industries to explain the FDIE WP and in 65% of industries to explain the HMTE WP. Contradictory evidence is found in only 15% and 25% of industries, respectively. Across industries, we find the most support on the extensive margin when applying our hypotheses to explain the FDIE WP, followed by the HMTE WP.

As a robustness check, we conduct the same hypothesis testing on the SOE WP, which we do not expect to be well-explained by our two hypotheses. These results are shown in Table A-3. We find support in our "best fit" regressions for the combined hypotheses applied to SOE WP in only 35% of industries and contradictory evidence in 54% of industries, confirming that the efficiency wage and fair wage hypotheses are less useful in explaining SOE WP.

So far our hypothesis testing has only examined the direction of changes in foreign WP, but we are also interested in the sizes of these changes. Table 6 presents results to address the question: how much of the benchmark foreign WP can be explained by the added wage determinants? We group the results based on the direction of change in the foreign WP and show mean percentage changes for industries with decreases (i.e., those satisfying (A) and (C)

[25] In 130 out of 147 industries the best-fit regression involved a combination of a profit variable and one or more of the training cost and technology variables. The variable combinations that produced the best-fit wage regression most often were "total profit, number of computers and training costs" (33 industries) and "operating profit, number of computers and training costs" (28 industries).

criteria) and the corresponding statistic for industries with increases (i.e., those satisfying (A) and (Z) criteria). Of the five variables tested, the two profit variables appear to be the strongest individual determinants of the foreign WP, on average. The FDIE coefficient fell by an average of 8.3% among the 92 industries that saw a decrease in the coefficient when total profits are included in the wage regression. The corresponding result for the HMTE coefficient is an average decline of 8.8% among 64 industries. When operating profits are included, the FDIE coefficient fell by an average of 6.7% across 95 industries and the HMTE coefficient declined by an average of 7.6% across 73 industries.

Among the training and technology variables, the strongest determinant of the foreign WP is the number of computers per worker. Adding the number of computers to the wage regression reduced the FDIE coefficient by an average of 5.2% across 106 industries and it reduced the HMTE coefficient by an average of 6.1% across 69 industries. Intangible assets appears to be another strong determinant of the FDIE WP, causing a 6.3% average decline in the coefficient but that average was strongly impacted by a single outlier case where the FDIE coefficient changed signs from positive to negative among the 39 industries showing a coefficient decline. Setting that outlier aside, intangible assets explained only 2.2% of the FDIE coefficient on average across 38 industries, and it explained only 1.3% of the HMTE coefficient on average across 22 industries. Similar to intangible assets, training cost was a weak determinant of the foreign WP, reducing the FDIE WP by only 2% on average in 22 industries and the HMTE WP by only 2.1% on average in only 9 industries.

Table 6 also shows the strength of our determinants when used in the best combination for each industry. In these best-fit wage regressions, our hypotheses combined can explain an average of 9% of the FDIE WP in 100 industries, and an average of 8.2% of the HMTE WP in

59 industries. However, we also generate on average 14.8% larger FDIE WP in 20 industries and 10.2% larger HMTE WP in 24 industries in our best-fit regressions. We conclude that our hypotheses combined explain just 9% of the FDIE WP in three-fourths of the industries that produced FDIE WP, and they explain slightly less of the HMTE WP in three-fifths of the industries that produced HMTE WP. Even after controlling for differences in profits, technology and/or training costs, we find large residual wage premia associated with foreign ownership in China in the vast majority of industries.

As a robustness test of these results on the strengths of WP determinants, we ask how much of the SOE WP is explained by our added technology and profit variables. These results are shown in Table A-4. Contrary to the results above for foreign WP, we find that per worker profit performs poorly as a determinant of the SOE WP while per worker training cost performs well. Total profit (operating profit) reduces the SOE WP in only 6 (9) industries by an average of 4.0% (8.5%) while training cost reduces it by 8.3% on average in 40 industries out of 59 industries producing a significant SOE WP. These results confirm that the most important determinants for foreign WP (i.e., profits and numbers of computers) differ from the most important determinant of SOE WP (i.e., training costs).

5. Conclusions

Controlling for observable differences in worker and firm characteristics within each 3-digit manufacturing industry in China, we find a significant wage premium attached to foreign ownership in 92% of industries and a wage premium attached to overseas-Chinese ownership in 62% of industries compared to private domestic ownership. FDIEs tended to generate larger wage premia across industries than HMTEs, but both types of foreign wage premia responded similarly in our tests of determinants. By comparison, wage premia generated by SOEs responded very differently in robustness checks of our results.

We find support for both the fair wage and worker turnover aversion (i.e., efficiency wage) hypotheses linking higher profits and higher technology at foreign firms relative to domestic firms to higher wages. Foreign firms tend to earn higher profits per worker and use more computers per worker than private domestic firms in most industries. Controlling for these variables in our wage regression helps to explain some of the foreign wage premium in many industries. We find per worker profit to be the strongest single determinant of foreign wage premia, explaining 7-8% of the FDIE wage premium in 72-75% of industries, and 8-9% of the HMTE wage premium in 76-77% of industries using either total profit or operating profit per worker in our wage regressions. The number of computers per worker helps to explain the foreign wage premium in 78% of industries for the FDIE wage premium and in 76% of industries for the HMTE wage premium, but it explains only 5-6% of these wage premia.

We do not find support for the efficiency wage hypothesis, however, when training costs and intangible assets were used as proxies for firms' worker turnover costs. Foreign firms tended to report higher intangible assets per worker than private domestic firms in most industries but this variable proved to be a significant determinant of the FDIE wage premium in only 29% of industries and a significant determinant of the HMTE wage premium in only 25% of industries, while explaining only 1-2% of either one on average, aside from one outlier case. Training cost per worker proved to be the worst determinant of foreign wage premia because the majority of firms reported spending nothing on worker training and foreign firms do not tend to spend more on worker training than private domestic firms in most industries. Instead of finding support for our hypothesis using this variable, we find contradictory evidence in most industries.

That is, controlling for training costs increased rather than decreased the foreign wage premium in the vast majority of industries.

When we combine our fair wage and efficiency wage hypotheses to tally our results using the best-fit wage regression for each industry, we can explain an average of 9% of the FDIE wage premium in 77% of the industries that produced a significant FDIE wage premium, and an average of 8% of the HMTE wage premium in 61% of the industries that produced a significant HMTE wage premium. Even after controlling for differences in profits, technology and/or training costs, we find large residual wage premia associated with foreign ownership in China in the vast majority of industries. We interpret these results as evidence that additional determinants not only matter for foreign wage premia but they matter in large ways. Further research is needed to explore these additional determinants of foreign wage premia.

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Table 1: Summary Statistics for Significant Firm Type and Exporter Type Wage Premia

	FDIE	HMTE	SOE	Collective	Exporter	PureExporter
Num. Positive & Sig.*	137	93	47	7	68	25
Num. Negative & Sig.*	1	0	12	16	2	20
Coefficient Mean	0.261	0.181	0.100	-0.037	0.101	0.032
Coefficient Median	0.250	0.155	0.141	-0.078	0.094	0.043
Coefficient Maximum	1.129	0.702	0.432	0.239	0.306	0.788
Coefficient Minimum	-0.268	0.053	-1.071	-0.354	-0.201	-0.425
Coefficients in Percentage Terms:						
Mean	0.298	0.199	0.105	-0.037	0.107	0.032
Median	0.284	0.168	0.152	-0.075	0.099	0.044
Maximum	2.091	1.017	0.540	0.270	0.358	1.200
Minimum	-0.235	0.055	-0.657	-0.298	-0.182	-0.346

Notes: From 149 3-digit manufacturing industries in China that met a minimum criterion for numbers of firms. The estimated coefficients for control variables in these benchmark regressions are summarized in Table A-1, along with regression statistics (i.e., adjusted R2 values, number of observations).

*Significant at least at the 10% level.

Table 2: Top-Ranked and Lowest-Ranked Industries by Wage Premia

Top 10	FDIE			HMTE			SOE		
	Ind.#	Ind	WP	Ind.#	Ind	WP	Ind.#	Ind	WP
1	332	Noble metals smelting	2.091	371	Railway transport equipment	1.017	299	Other rubber products	0.540
2	347	Enamel produts	1.253	332	Noble metals smelting	0.619	334	Non-ferrous metals	0.530
3	361	Mining, metallurgy equipment	0.653	322	Steel smelting	0.501	282	Synthetic fibers	0.469
4	412	Precision instruments	0.607	299	Other rubber products	0.409	322	Steel smelting	0.463
5	133	Vegetable oil processing	0.584	276	Biological, biochem. products	0.364	349	Misc. metals products	0.420
6	363	Food, bev., feed manuf. equip.	0.553	363	Food, bev., feed manuf. equip.	0.343	323	Iron-rolling	0.417
7	353	Cranes & transporters	0.549	277	Hygenic, medicinal & pharmaceutica	0.334	429	Misc. manufacturing	0.367
8	251	Refined petroleum products	0.503	295	Daily-use & medical rubber products	0.332	413	Watches & timing instruments	0.338
9	401	Communication equipment	0.491	263	Pesticides	0.328	241	Stationary, pens, educational models	0.314
10	316	Fireproof materials	0.485	133	Vegetable oil processing	0.323	397	Lighting tools	0.294
Bottom 10									
10	405	Electron devices	0.128	136	Aquatic products processing	0.102	152	Beer, wine, spirits	-0.076
9	421	Handicrafts	0.128	342	Metallic tools	0.099	135	Meat processing	-0.080
8	182	Textile fabric shoes	0.114	272	Chemical medicines	0.098	313	Bricks, tiles, stones for construction	-0.099
7	394	Batteries	0.108	204	Bamboo, rattan, palm, grass prod.	0.096	134	Sugar	-0.099
6	145	Canned foods	0.106	307	Plastic parts	0.094	267	Soaps, toothpaste, perfume	-0.121
5	172	Wool textile, dyeing & finishing	0.104	175	Textile products	0.093	345	Metallic construction & safety prod.	-0.201
4	414	Optical instruments, spectacles	0.104	176	Knitwear & woven products	0.083	315	Ceramic products	-0.204
3	244	Toys	0.088	406	Electronic components	0.082	363	Food, bev., feed manuf. equip.	-0.258
2	137	Vegetables, fruits, nuts processing	0.081	192	Leather goods	0.074	374	Bicycles	-0.349
1	322	Steel smelting	-0.235	313	Bricks, tiles, stones for construction	0.055	244	Toys	-0.657

Notes: Only wage premia significant at least at 10% level included in these rankings; WP=wage premium in percentage terms.

Table 3: Correlations between Average Firm Variables by Industry and Wage Premia by Industry

Correlations:	FDIE	HMTE	SOE	Collective
Firm Age	0.319	0.457	-0.064	0.221
Total Labor	-0.268	0.289	-0.011	-0.088
Total Assets	-0.135	0.330	0.210	-0.075
Gross Industrial Output	-0.073	0.269	0.186	-0.158
Fixed Assets	-0.191	0.299	0.204	-0.061
Average Years Education	0.332	0.330	0.189	0.118
Higher Educated Share	0.313	0.292	0.174	0.078
Female Share	-0.386	-0.373	-0.176	-0.178
Export Probability	-0.344	-0.391	-0.228	-0.399
Export Share of Sales	-0.358	-0.376	-0.278	-0.340
Wage per Worker	0.284	0.237	0.187	-0.036
Allowance per Worker	0.384	0.405	0.236	0.178
Compensation per Worker	0.325	0.297	0.208	0.027
Fixed Assets per Worker	0.094	0.152	0.262	0.048
Intangible Assets per Worker	0.132	0.200	0.115	0.277
Training Cost per Worker	0.374	0.248	0.181	0.401
Num. Computers per Worker	-0.010	-0.026	0.098	-0.009
Total Profit per Worker	0.415	0.229	0.230	0.303
Operating Profit per Worker	0.431	0.224	0.190	0.265
#significant wage premia	138	93	59	23

Table 4: Hypothesis Testing Results for Question (i) using Summary Statistics by 3-Digit Industry

Per worker:	Training cost	Intangible Assets	Num. computers	Total profit	Operating profit
Number of industries where FDIE statistic > PDE statistic					
Mean	82	110	134	102	107
Median	30	93	137	105	101
75th percentile	59	131	138	127	124
Number of industries where HMTE statistic > PDE statistic					
Mean	31	91	118	69	74
Median	16	48	132	63	56
75th percentile	24	123	126	90	94

Per worker:	Training cost	Intangible Assets	Num. computers	Total profit	Operating profit
Shares of 149 industries where FDIE statistic > PDE statistic					
Mean	0.550	0.738	0.899	0.685	0.718
Median	0.201	0.624	0.919	0.705	0.678
75th percentile	0.396	0.879	0.926	0.852	0.832
Shares of 149 industries where HMTE statistic > PDE statistic					
Mean	0.208	0.611	0.792	0.463	0.497
Median	0.107	0.322	0.886	0.423	0.376
75th percentile	0.161	0.826	0.846	0.604	0.631

Table 5: Hypothesis Testing Results for Question (ii) using Wage Regressions for Each 3-Digit Industry with Added Variables

	Bench-mark (1)	Training Costs (2)	Intangible Assets (3)	Num. Computers (4)	Bench.: Total profit≥0 (5)	Total Profit (6)	Bench.: Op. profit≥0 (7)	Operat-ing Profit (8)	Best fit (9)
Num. ind. w/added variable sig. & positive		129	32	122		129		130	--
Num. ind. w/added variable sig. & negative		0	4	0		0		2	--
Num. ind. w/improved regression fit* (A)		124	66	123		124		123	142
FDIE Coefficients:									
Num. ind. w/FDIE coeff. sig. & positive	137	137	134	133	129	128	129	128	127
Num.ind. w/FDIE coeff. sig. & negative	1	1	2	2	0	1	1	1	0
Num. ind. satisfying (A) & (B)		0	1	2		1		3	4
Num. ind. satisfying (A) & (C)		22	39	106		92		95	100
Num. ind. satisfying (A) & (Z)		94	23	8		17		15	20
Share of ind. satisfying (A) & (B) or (C)**		0.159	0.290	0.783		0.721		0.754	0.800
Share of ind. satisfying (A) & (Z)**		0.681	0.167	0.058		0.132		0.115	0.154
HMTE Coefficients:									
Num. ind. w/HMTE coeff. sig. & positive	93	96	95	89	90	90	97	96	94
Num.ind. w/HMTE coeff. sig. & negative	0	0	0	1	0	0	0	0	1
Num. ind. satisfying (A) & (B)		1	1	2		4		2	4
Num. ind. satisfying (A) & (C)		9	22	69		64		73	59
Num. ind. satisfying (A) & (Z)		72	19	9		12		9	24
Share of ind. satisfying (A) & (B) or (C)***		0.108	0.247	0.763		0.756		0.773	0.649
Share of ind. satisfying (A) & (Z)***		0.774	0.204	0.097		0.133		0.093	0.247
Total #firms	244,397	244,396	244,393	244,399	194,641	194,617	190,473	190,465	varies

Notes:

Criterion (B) = firm type coeff. changed from significant to insignificant with added variable(s) included in the regression.

Criterion (C) = firm type coeff. declined but remained sig. with added variable(s) included in the regression.

Criterion (Z) = firm type coeff. increased but remained sig. with added variable(s) included in the regression.

*Improved regression fit measured by an increase in adjusted-R2 after new variable added.

**Shares out of 138 (129 or 130) industries with significant FDIE coeff. in respective benchmark regressions.

***Shares out of 93 (90 or 97) industries with sig. HMTE coeff. in respective benchmark regressions.

Table 6: How much of the foreign wage premiums are explained by the added variables?

Per Worker:	Training Costs	Intangible Assets	Intang. Assets--w/out outlier*	Num. Computers	Total Profit	Operating Profit	Best Fit
FDIE Coefficients:							
Mean %Δ in FDIE coeff. for ind. w/decrease	-0.020	-0.063	-0.022	-0.052	-0.083	-0.067	-0.090
Mean %Δ in FDIE coeff. for ind. w/increase	0.058	0.031	0.031	0.022	0.044	0.018	0.148
Min. %Δ in FDIE coeff.	-0.071	-1.625	-0.177	-0.199	-0.244	-0.253	-0.253
Max. %Δ in FDIE coeff.	0.694	0.147	0.147	0.064	0.494	0.062	0.966
Num. ind. satisfying (A) & (C)	22	39	38	106	92	95	100
Num. ind. satisfying (A) & (Z)	94	23	23	8	17	15	20
HMTE Coefficients:							
Mean %Δ in HMTE coeff. for ind. w/decrease	-0.021	-0.013	-0.013	-0.061	-0.088	-0.076	-0.082
Mean %Δ in HMTE coeff. for ind. w/increase	0.102	0.026	0.026	0.015	0.076	0.040	0.102
Min. %Δ in HMTE coeff.	-0.060	-0.030	-0.030	-0.235	-0.298	-0.285	-0.248
Max. %Δ in HMTE coeff.	0.875	0.116	0.116	0.053	0.234	0.099	0.429
Num. ind. satisfying (A) & (C)	9	22	22	69	64	73	59
Num. ind. satisfying (A) & (Z)	72	19	19	9	12	9	24

Notes: mean %change=(coefficient after added variable inclusion - benchmark coefficient)/ABS(benchmark coefficient)

ABS=absolute value

*Outlier result for industry 332 (Noble metals smelting) with %Δ in FDIE coeff. of -1.625, with coeff. changing from 1.129 to -0.705 with added variable.

Table A-1: Benchmark Regressions Statistics for 149 3-digit Industries

	Estimated Coefficients for Centered Control Variables:				**Regression Statistics:**	
	K-intensity	**Total L**	**Avg. Education**	**Female Share**	**adj. R2**	**Observations**
Num. Positive & Sig.*	144	91	129	3	--	--
Num. Negative & Sig.*	0	2	1	77	--	--
Mean	0.058	0.049	0.766	-0.001	0.401	1,640
Median	0.057	0.044	0.673	-0.001	0.405	1,164
Maximum	0.129	0.149	2.000	0.004	0.676	10,972
Minimum	0.025	-0.077	-0.537	-0.005	0.142	203

Notes: Mean, median, maximum and minimum values for significant coefficients only.
*Significant at least at the 10% level.

Table A-2: Summary Annual Wage Statistics for 149 3-digit Industries

	Annual Wage	
	Mean	**Standard dev**
Mean	13.3	12.8
Median	12.8	11.8
Maximum	26.7	28.3
Maximum Ind.#	401	401
Maximum Ind. Name	Communication equipment	
Minimum	8.6	5.1
Minimum Ind.#	173	173
Minimum Ind. Name	Natural fibers	

Notes: Currency amounts in thousands of yuan.

Table A-3: Robustness Tests for Question (ii) using SOE Wage Premia

	Bench-mark (1)	Training Costs (2)	Intangible Assets (3)	Num. Computers (4)	Bench.: Total profit≥0 (5)	Total Profit (6)	Bench.: Op. profit≥0 (7)	Operating Profit (8)	Best fit (9)
Num. ind. w/added variable sig. & positive		129	32	122		129		130	--
Num. ind. w/added variable sig. & negative		0	4	0		0		2	--
Num. ind. w/improved regression fit* (A)		124	66	123		124		123	142
SOE Coefficients:									
Num. ind. w/SOE coeff. sig. & positive	47	43	50	52	57	71	56	60	65
Num.ind. w/SOE coeff. sig. & negative	12	13	11	10	9	6	12	9	8
Num. ind. satisfying (A) & (B)		7	0	2		2		5	6
Num. ind. satisfying (A) & (C)		40	9	19		6		9	18
Num. ind. satisfying (A) & (Z)		6	19	31		51		47	37
Share of ind. satisfying (A) & (B) or (C)**		0.797	0.153	0.356		0.121		0.206	0.353
Share of ind. satisfying (A) & (Z)**		0.102	0.322	0.525		0.773		0.691	0.544
Total #firms	244,397	244,396	244,393	244,399	194,641	194,617	190,473	190,465	varies

*Improved regression fit measured by an increase in adjusted-R2 after new variable added.

**Shares out of 59 (66 or 68) industries with significant SOE coefficient in respective benchmark regressions.

Table A-4: Robustness Tests: How much of the SOE wage premiums are explained by the added variables?

Per Worker:	Training Costs	Intangible Assets	Num. Computers	Total Profit	Operating Profit	Best Fit
SOE Coefficients:						
Mean %Δ in SOE coeff. for ind. w/decrease	-0.083	-0.029	-0.045	-0.040	-0.085	-0.082
Mean %Δ in SOE coeff. for ind. w/increase	0.032	0.033	0.087	0.163	0.164	0.151
Min. %Δ in SOE coeff.	-0.346	-0.123	-0.110	-0.059	-0.258	-0.317
Max. %Δ in SOE coeff.	0.062	0.113	0.281	0.601	0.525	0.370
Num. ind. satisfying (A) & (C)	40	9	19	6	9	18
Num. ind. satisfying (A) & (Z)	6	19	31	51	47	37

Notes: mean %change=(coefficient after added variable inclusion - benchmark coefficient)/ABS(benchmark coefficient)
ABS=absolute value