Do Multinationals Transfer Culture? Evidence on Female Employment in China*

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(Preliminary. Please do not circulate. Comments are welcome.)

Abstract

This paper studies empirically whether and how multinational firms transmit corporate culture across countries. We focus on a specific aspect of culture – social norms towards women in labor markets. Using Chinese manufacturing firm data over the period of 2004-2007, we find that foreign affiliates whose home countries' culture is more favorable for women tend to hire proportionately more women and are more likely to appoint female managers. Foreign affiliates, especially those from countries with a more pro-women culture, also generate cultural spillover to domestic firms, as revealed by a positive correlation between domestic firms' female employment shares and the prevalence of foreign direct investment (FDI) across industries or cities. To quantitatively analyze the productivity loss due to gender inequality, the mechanism of cultural spillover, and its associated productivity gains, we build a parsimonious multi-sector task-based model that features firm heterogeneity in productivity and biases towards female workers, as well as women having a comparative advantage in skill- rather than physically-intensive tasks. We then confront several model predictions using the firm data. Consistent with the model predictions, we find evidence that domestic firms respond to increased FDI by hiring more women, due to more intense competition and imitation. Such cultural spillover is stronger in sectors in which women have a comparative advantage and for the less productive firms. Quantitative analysis suggests large aggregate productivity loss due to gender inequality and potentially large productivity gains from cross-border cultural spillover.

Key Words: cultural spillover, gender inequality, FDI, misallocation
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1 Introduction

Multinational firms are an important driving force of globalization and economic convergence between countries. An extensive literature shows that multinationals bring technology, knowledge, and different sorts of capital to host countries.[1] In addition to economic benefits, scholars and journalists have long been writing about cross-country cultural spillover and convergence due to foreign direct investment (FDI). Some of the discussions were controversial.[2] The economics literature has so far been relatively silent about the cultural effects of FDI. Part of the reasons is that quantifying culture is difficult, let alone identifying its diffusion.

This paper contributes to the debate about the cultural effects of economic globalization by studying how multinationals may change a specific aspect of a country's culture – gender norms in the labor market. Different from recent studies that focus on the effects of international trade on gender inequality (e.g., Black and Brainerd, 2004; Juhn et al., 2013, 2014), we examine instead the effects of FDI. Specifically, we study whether and how multinational firms, based on their home countries' overall attitude towards women, transmit corporate culture across border, as revealed by the changes in female employment shares in both affiliates and domestic firms. We use comprehensive manufacturing firm data from China over the period of 2004-2007, together with a unique data set on the country of origin of each foreign-invested enterprise (FIE) to document the facts about cultural transfer within multinational firm boundary and cultural spillover to domestic firms. Based on the recent literature on resource misallocation (Hsieh and Klenow, 2009; Hsieh et al., 2013), we then quantify the aggregate productivity cost of gender discrimination and the economic benefit of cultural spillover from FDI, an aspect of spillover that has been overlooked in the literature.

We find that compared to domestic Chinese firms, FIEs tend to hire proportionately more women and are more likely to appoint female managers (see Figures 1 and 2 for the pattern). The magnitude of cultural transfer is larger for FIEs whose home countries' culture is more favorable for women, inferred from both perception-based (from World Value Survey) and outcome-based (from United Nations Development Program) measures of countries' gender gap. Specifically, we find that a one standard deviation decrease in the outcome-based measure of gender inequality (reducing Malaysia's gender inequality to that of Germany) is associated with a 1.9 percentage-point higher female employment share in the affiliate on average, within a narrowly defined industry

[1] See Aitken and Harrison (1997), Javorcik (2004), Branstetter (2006), and Keller and Yeaple (2009), and a comprehensive literature review by Harrison and Rodriguez-Clare (2010), among others.

[2] Pieterse (2003) and Hopper (2007) study how economic globalization can reshape the culture of the participating countries. They examine three paradigms: clash of civilizations, McDonaldization, and hybridization. Friedman's best-selling book *The Lexus and the Olive Tree: Understanding Globalization* (1999) postulates that "No two countries that both had McDonald's had fought a war against each other since each got its McDonald's". While the hypothesis may have been invalidated since the book was published over a decade ago, but the idea is succinct.

and province (see Figure 3 for an illustration).

In addition to corporate cultural transfer within firm boundary, we find evidence of cultural spillover – the prevalence of FIEs in the same market (narrowly defined industry or city) is positively correlated with domestic Chinese firms' female employment shares and their likelihood of having a female manager. By exploiting the firm panel data, we obtain such positive correlation even after controlling for industry, province, and firm fixed effects. In particular, controlling for firm fixed effects, we find that a one standard deviation increase in the foreign share of an industry's output is associated with a 0.7 percentage-point increase in a domestic firm's share of female workers in the same industry on average. Once again, we find stronger cultural spillover from FIEs whose countries of origin have a more pro-women culture, suggesting that the changes in domestic firms' female employment shares are not purely driven by increased competition (in either goods or labor markets). The results on cultural spillover remain robust to controlling for a wide range of firm characteristics, including skill intensity and technology.

To quantitatively analyze the productivity loss due to gender inequality, the mechanism of cultural spillover, and its associated productivity gains, we build a parsimonious multi-sector task-based model (a la Acemoglu and Autor, 2011) that features firm heterogeneity in productivity and biased perceptions about female labor productivity. The model focuses on firms' labor demand and assumes inelastic labor supply by both female and male workers.[3] In the model, sectors differ in the intensity of physically-intensive tasks and skilled tasks, in which women have a comparative advantage. We explicitly incorporate in the model features of statistical discrimination (Phelps, 1972 and Arrow, 1973). Firms draw both productivity and perception about female labor productivity before entering a market. Those from countries with a more pro-women culture draw the perceived female labor productivity from a distribution, which has a higher mean but a lower variance. A biased perception towards women leads to a suboptimal level of female employment, reducing profits. We find evidence supporting this hypothesis, implying that gender discrimination is costly. A contribution of the model is that we can express production functions micro-founded on tasks with varying skill intensities ultimately as those that feature a constant elasticity of substitution between female and male labor. This theoretical result permits an empirical examination of firms' gender biases even when information on task inputs of a firm is not available.

We then model cultural spillover as a process of domestic firms' updating their (biased) belief about female labor productivity towards the true value, as in a standard social learning model (a

[3] Our empirical results show a weakly negative correlation between the prevalence of FDI and wages in the same city, alleviating the concern that foreign firms bid up wages and increase female labor supply or female internal migration.

la Jovanovic, 1982).[4] A firm updates its information (learn) more if its prior belief about female labor productivity is more different from foreign firms, if there are more foreign firms that are less biased against women, or if the precision of information (signals) from foreign firms is lower. We find supporting evidence for all these predictions using our firm data. Moreover, as predicted by the model, we find that both cultural transfer and spillover are stronger in sectors in which women have a comparative advantage in production.

The entry of foreign firms raises competition, forcing the more discriminating domestic firms to exit the market due to lower profits. In other words, despite our theoretical focus on statistical discrimination, our model delivers results that resonate with the predictions by the models on taste-based discrimination (a la Becker, 1957), as in a heterogeneous-firm model, increased competition due to foreign firm entry would induce the more discriminating domestic firms to either raise female employment or exit the market. Our regression analysis confirms Becker's hypothesis by showing that firms with a higher female employment share is less likely to exit the market in response to an increase in FDI in the same market. This negative correlation is more significant if the FDI is from countries with a more pro-women culture, or in sectors in which female comparative advantage is larger. Therefore, domestic firms' adjustments of employment by gender at both the intensive margin due to learning and the extensive margin due to exits contribute to the convergence of firms' female employment shares to the optimal one, reducing the misallocation of resources in the economy and increasing aggregate productivity. We then use the model to quantify the cost of gender discrimination in China. Based on the literature on resource misallocation (e.g., Hsieh and Klenow, 2009; Hsieh et al., 2014; Joel, Hopenhayn, and Venkateswaran, 2015), we find a substantial loss in aggregate total factor productivity due to gender biases, and a non-negligible gains of cultural spillover from foreign firms. *[to be completed]*

This paper contributes to several strands of literature crossing broad social science disciplines. It contributes to the literature on the historical roots of gender inequality (e.g., Qian, 2008; Guiso, Sapienza and Zingales, 2006; Alesina, Giuliano, and Nunn, 2013; Edlund et al., 2013).[5] Confucius philosophy, the foundation of Chinese culture, advocates the strict obligatory role of women. In the traditional Chinese patriarchal society, males were viewed as superior and women were expected to follow the leadership of the males in the family, typically the father before marriage and the husband afterwards. After the People's Republic of China was founded in 1949, gender inequality

[4] Subsequent studies about learning and diffusion of ideas include Foster and Rosenzweig (1995), Conley and Udry (2010), and Moretti (2011). See Foster and Rosenzweig (2010) for a review of the literature.

[5] The gender prejudice has been shown to have significant impact on China's macroeconomic outcomes, such as saving, investment, economic growth, and housing prices (Du and Wei, 2012; Wei and Zhang, 2011a; Wei and Zhang, 2011b). Instead of studying the consequences of discrimination, we provide evidence that FDI can be used as a vehicle to change social norms.

was significantly reduced under Mao's egalitarian philosophy.[6] The female labor force participation rate soared, with more women becoming government leaders and role model workers in state-owned enterprises. However, this period of women empowerment ended when the government introduced market-oriented economic reforms since the early 1980s, with gender inequality widening since (e.g., Gustafsson and Li, 2000; Cai, Zhao and Park, 2008; Zhang et al., 2008).[7]

Our paper also adds to the large body of work on the relation between globalization and culture (e.g., Hofstede, 1980; Pieterse, 2003; and Hopper, 2007).[8] Our paper provides empirical support for these pure theories or case studies about the "cultural convergence" hypothesis. Recent research in economics empirically examines specific channels through which cultural values can be passed from one country to another (Fisman and Miguel, 2007; Maystre et al., 2014). Related to gender issues, research shows that making progress has been shown to be challenging, as prejudices against certain groups in society often have their deep historical roots (Roland, 2004; Jayachandran, 2014). Our paper shows how a fast globalization event can affect slow-moving cultural norms.

Given the paper's focus on firms' revealed preferences for women, the paper is naturally related to the extensive literature on discrimination (Rhode, 1991; Altonji and Blank, 1999; Almond and Edlund, 2008; Wei and Zhang, 2011a; Duflo, 2012; Iyer et al., 2012; Autor and Wasserman, 2013). Recent research in economics quantitatively assesses the cost of discrimination (Mortvik and Spant, 2005; Cavalcanti and Tavares, 2007; Hsieh et al., 2013). Hsieh et al. (2013) find that 15 to 20 percent of the growth of aggregate output per worker from 1960 to 2008 could be explained by increasingly more efficient allocation of talent independent of gender and race.[9] Complementing their findings, we provide the first piece of firm-based evidence on the cost of discrimination. Our paper suggests that external forces such as FDI can help alleviate gender inequality in a relatively short run. The classic book by Becker (1957) hypothesizes that firms that discriminate against a particular group will be driven out of business in the long run by firms that discriminate less. Several studies have verified Becker's hypotheses in the context of trade (Black and Brainerd, 2004; Juhn, Ujhelyi, and

[6] For instance, in 1950s, women won the right to own property and land and the right to vote. Women won the freedom to marry and divorce for the first time in Chinese history after the marriage law was passed in 1950.

[7] According to a survey conducted by the Center for Women's Law and Legal Services at Peking University over 3,000 women in 2009: More than 20 percent say employers cut salaries on women who become pregnant or give birth, and 11.2 percent lose their jobs for having a baby. More than one third of the surveyed women believe that male employees have more opportunities than women in getting promotion.

[8] Social psychologist Hofstede (1980) shows how a country's culture is multi-dimensional and is determined by both internal and external forces. Sociologists Pieterse (2003) and Hopper (2007) study how economic globalization can change participating countries' culture. They examine three paradigms: clash of civilizations, McDonaldization and hybridization. Using McDonald's as an example of FDI cultural transfer, Friedman (1999) argues that "No two countries that both had McDonald's had fought a war against each other since each got its McDonald's".

[9] Also see a recent report by the McKinsey Global Institute (2015) about the economic cost of gender biases in different countries. Using Japanese firm data. Kawaguchi (2007) finds that the impact of gender discrimination on firm profits and growth is small.

Villegas-Sanchez, 2013, 2014).[10] We study instead the effects of foreign direct investment (FDI) on the gender gap in the labor market.

Finally, as already stated in the opening paragraph, our paper contributes to the extensive literature on economic benefits, in particular technology spillover, associated with FDI (e.g., Aitken and Harrison, 1997; Javorcik, 2004; Branstetter 2006; Keller and Yeaple, 2009, among others). Our paper shows an unexplored type of FDI spillover.

The rest of the paper proceeds as follows. Section 2 discusses our data source, measurement issues, and empirical evidence. Section 3 introduces our theoretical model. Based on our theory, Section 4 tests the model predictions about the transfer and spillover of cultural values regarding female employment. Section 5 quantifies the aggregate productivity loss due to gender discrimination and gain from FDI cultural spillover. The last section concludes.

2 Data and Empirical Evidence

2.1 Data

2.1.1 Firm-Level Data

The primary data for our analysis are drawn from the annual industrial firm surveys of China over the period of 2004-2007. The surveys are conducted by the country's National Bureau of Statistics (NBS). The data cover all state-owned firms, and all non-state firms that have sales over 5 million RMB (about 0.7 million USD at the 2007 exchange rate). Detailed firms' balance sheet information, such as output, value added, detailed industry code (482 categories), exports, employment, value of intermediate inputs, as well as address and registered ownership type (foreign or domestic in particular) are available. Despite the sales threshold, the data are fairly representative. For 2004, the aggregate data based on our firm data accounted for 91, 71, 97, and 91 percents of China's total industrial output, employment, exports, and fixed assets, respectively. To construct a panel data set, we use unique firm ID to identify the same firm across years.[11]

Most importantly, we use the following firm variables about the gender of workers in our analysis:

1. For 2004, we use information on firm employment by gender and education levels.[12] While

[10] Black and Brainerd (2004) find that competition due to trade liberalization lowers the gender wage gap in the U.S. Juhn, Ujhelyi, and Villegas-Sanchez (2013, 2014) show that trade liberalization in Mexico reduces gender inequality, especially among blue collar workers, as the intensive use of machines by new exporters replaces physically demanding tasks, for which male workers have a comparative advantage.

[11] There are situations when a firm's ID of the same firm changes over time, due possibly to restructuring or merger and acquisition. To resolve this data discrepancy, we use firms' name, sector, and address to complement the use of firm ID to identify firms over time.

[12] 2004 is a census year and has richer information than other years. Notice that the sample for 2004 that we use is from the "above scale" part of the census.

information on the number of workers in a firm by different levels of education are available, in this paper, we consider a worker as skilled if s/he has education of senior high school or above. Based on this definition, 39 percent of total employment in our data set are considered skilled workers in 2004.[13]

2. For years between 2005 and 2007, we have employment by gender but not by education levels.

Notice that our data do not provide a wage breakdown by gender. With this limitation, we focus on studying gender gap as revealed by different employment shares across firms. In Section 4, we will provide information about the effects of FDI on the male wage premium across cities. The goal of the wage regressions is to rule out the labor supply effects, due to potentially more women supplying labor in industries or cities where there is more FDI. We use information on firms' registration types to identify the foreign ownership status of a firm.

Information about the country of origin of each FIE is obtained from several *Foreign Invested Firms Surveys* conducted by China's Ministry of Commerce (MOFCOM). We merge the MOFCOM country of origin data with the NBS firm survey data, using firm names and other contact information. We exclude the ethnic Chinese FIEs (those with main investors from Hong Kong, Macau and Taiwan), as it is not possible to identify cultural difference between investors from those economies and China. About 52% of non-ethnic Chinese FIEs in the 2004 industrial survey data can be merged with the MOFCOM country of origin data.

2.1.2 Identifying the Gender of Managers

Prejudice against women might be greater at a higher level of a firm's hierarchy. This is often referred to as the "glass ceiling" effect, which prevents women from taking senior-level management positions (Nevill et al., 1990). Does cultural transfer also affect firms' appointment of female managers? In other words, are foreign parent firms from countries with greater gender equality more likely to employ women as managers of their affiliates?

To answer these questions, we need information about the gender of the manager in each firm. Unfortunately, such information is not available. To overcome this problem, we come up with a novel method to identify the gender of a firm's manager. The method relies on the last character of the name of the legal representative of each Chinese firm in our database to infer the femininity (or masculinity) of each name.[14] To this end, we first build a database that quantifies the degree

[13] An alternative definition of skilled labor is college and above. Under this definition, skilled labor accounts for 9 percent of the total employment in 2004. Our results are robust to this alternative definition.

[14] In China, the legal representative of a firm is typically the CEO, president, or general manager of the firm. Most Chinese names are composed of two characters, so the last character can be considered as a equivalence to the first name in the Anglo-Saxon world.

of femininity (masculinity) of a Chinese name character. The database is built from a random sample of China's 2005 1% population census, which contains 2.5 million names and their gender information.[15] Specifically, for each Chinese character, we calculate the probability that it is used in a female name based on our name database, using the following formula:

$$female\_prob_i = \frac{freq\_female_i}{freq\_female_i + freq\_male_i}, \tag{1}$$

where $freq\_female_i$ ($freq\_male_i$) is the number of times that character i appears as the last character in a female (male) name. Table A2 in the appendix list the ten most frequently used Chinese characters that appear as the last characters of both female and male names, respectively. For the top 10 most commonly used characters in female names, the probability that the character is used by a man is always smaller than 1%.

2.1.3 Country-Level Data

To measure country-level gender-related culture, we use the following two data sources. The first data source, which is often used in the studies of cross-country gender issues, is from the United Nations Development Program (UNDP). The UNDP provides a set of indicators for gender inequality across 149 countries. In this study, we use the Gender Inequality Index (GII), which is a composite index capturing the loss of women's achievement due to gender biases. This index focuses on three dimensions: reproductive health, empowerment, and labor market participation. A higher GII value indicates greater gender inequality. We use the 2012 Gender Inequality Index. As Panel A of Table 1 shows, countries with the lowest GII are Sweden, Denmark, Netherlands, Norway and Switzerland. Countries with the highest GII include Iraq, Yemen, Afghanistan, Niger and Mali. Obviously, a country's GII is correlated with its income level. But there are rich countries that score very high in GII (such as Saudi Arabia) and poor countries that score very low in GII (such as the Philippines). In our regression analysis, we will always control for countries' income level and other common characteristics.

As a robustness check, we supplement the GII index with data from the World Value Survey (WVS), which provides subjective survey-based measures of gender-related perceptions and beliefs. We use the 2005 wave of WVS, which contains data for 53 countries. We collect data from the following three questions:

- Question V44 "Men should have more right to a job than women";
- Question V61 "On the whole, men make better political leaders than women do";

[15] We restrict our sample to the people who were aged between 35 and 65 in 2005.

- Question V63: "Men make better business executives than women do".

There are three choices to answer Question V44: "agree", "neither" and "disagree". We calculate the individual score by assigning 0, 0.5 and 1 to these three choices, respectively. The country score of V44 is the average score over all individuals in that country. Questions V61 and V63 have four choices: "strongly agree", "agree", "disagree" "strongly disagree". We assign 0, 0.33, 0.67 and 1 to these choices. Again, we calculate the country means of V61 score and V63 score. The country WVS score is simply the average of V44, V61 and V63 scores. Higher WVS score indicates lower gender inequality. Based on our calculation, Panel B of Table 1 shows that countries with the five highest WVS score are Sweden, Norway, France, Finland and Canada. Countries with the lowest WVS scores are Egypt, Jordan, Mali, India and Iran. The WVS indices are highly correlated with GII across countries.

The GII and WVS data do not provide gender inequality measures for Hong Kong and Taiwan, two of the largest sources of FDI in China. However, given that the major population of the two economies are ethnic Chinese and are highly adaptive to the local culture, their employment preferences may not reflect their underlying gender inequality. Moreover, whether we should treat investment from Hong Kong and Taiwan as FDI is debatable. The data limitation forces us to drop firms from these two economies, but we would have chosen to do so even if we had the data.

Table A1 in the appendix defines and describes all variables used in the analysis. Table 2 reports the summary statistics of key variables used in the analysis at the country, industry, city and firm levels. Average female employment share of the FIEs (excluding Hong Kong, Macau and Taiwan firms) is 0.482, which is much higher than that of the Chinese local firms (0.390). FIEs are also more likely to hire women as managers. Table 2 also shows a significantly higher female share in employment on average and a higher probability of appointing a woman as the manager among FIEs. Figure 1, which plots the kernel density of female employment shares for both domestic firms and FIEs in 2004, confirms this result in a distribution sense. To partially address the concern that FIEs are distributed unevenly across sectors, due to their comparative advantage in different industries, Figure 2 plots the kernel density of female employment shares after controlling for 4-digit industry fixed effects (482 categories). It confirms that the distributional differences in female employment shares does not seem to be driven by the differential prevalences of domestic and foreign firms across narrowly defined industries.[16]

[16] One can argue that even within a narrow industry, there is still a wide range of activities that the domestic and foreign firms may specialize in differently. In the regression analysis below, we will control for a host of firm-level technology measures to partially address this potential within-industry variation.

2.2 Empirical Evidence

2.2.1 Evidence on Cross-Border Cultural Transfer

We first examine the existence of cultural transfer within firms – that multinational firms carry their headquarter's employment practices to their Chinese affiliates and change their female shares in employment.

To investigate the gender cultural transfer from foreign parents to their affiliates in China, we estimate the following specification using the 2004 data:

$$\left(\frac{f}{f+m}\right)_{ic} = \beta_0 + \beta_1 GII_c + \beta_2 \ln(GDP/Pop)_c + \mathbf{X}'_{ic}\boldsymbol{\gamma} + \{FE\} + \varepsilon_{ic}, \tag{2}$$

where $\left(\frac{f}{f+m}\right)_{ic}$ stands for the share of female workers in firm i from foreign country c, or a dummy indicating whether the firm's general manager is a woman.[17] GII_c is a measure of gender inequality in country c, as described in the previous section. $\ln(GDP/Pop)_c$ is log GDP per capita of country c. $\mathbf{X}_{ic}$ is a vector of firm i's characteristics (see below). See Table A1 in the appendix for the definitions and data sources for each of these variables. $\{FE\}$ includes four-digit industry (482 categories) and province (31 regions) fixed effects. ε_{ic} is the error term.

The main challenge in the empirical analysis is to control for all confounding factors that affect a firm's decision to hire women. In eq. (2), we include home country (log) GDP per capita as a regressor to hopefully control for a wide range of potential determinants of female employment related to the investing country's stage of development. We also control for a host of firm-level variables ($\mathbf{X}_{ij}$), which according to existing research, should affect female employment. In particular, to the extent that investments in capital, technology, and automation in production lead to a reduction in the demand for physically demanding tasks (Juhn, Ujhelyi, and Villegas-Sanchez, 2014), technology transfer from advanced economies and the induced investment may complement female labor. To this end, we include as regressors the foreign affiliate's choices of technology, mesaured by its computer intensity, R&D intensity, (log) TFP, skill intensity, and (log) capital intensity. We also control for the firm's wage rate and (log) output. The former is to address the concern that foreign firms may take advantage of the lower average wage of female workers and hire more of them,[18] while the latter is to take into account any scale effect on female employment.[19]

[17] In China, all registered companies need to appoint a legal representative for the firm, who will be responsible for all legal matters of the company. Such legal representative are oftentimes the general manager or CEO of the company.

[18] The evidence on the negative wage premium for women based on Mincer wage regressions using China's urban household survey data are available upon request. For evidence for how foreign firms may take advantage of the host country's biases against women and enter the market, see Siegel, Kodama, and Halaburda (2014).

[19] For instance, if a larger firm requires more management inputs, and women have a comparative advantage in

We also control for the age of the affiliate to deal with the potential assimilation effect. In the initial years of operation in China, a foreign firm may bring its home country's culture to the host country. Such cultural transfer, however, may dissipate over time if the affiliate assimilates itself with the local environment and behave more like a domestic firm. This hypothesis would imply a negative relationship between a foreign firm's female employment share and age. As China's social and legal environments differ significantly across regions, we also include province fixed effects to control for time-invariant province-specific factors that affect foreign firms' location decisions and female employment. To deal with the correlation between female comparative advantage (see below) and firms' female employment shares across industries, we control for 4-digit industry fixed effects. Notice that our regression sample includes only FIEs and excludes domestic firms. Thus, identification comes primarily from the variation in multinational headquarters' home countries' gender norms, rather than from the mean difference between domestic and foreign firms.

Table 3 reports the regression results. In column (1), controlling for province and 4-digit industry fixed effects, we find a negative and fairly significant (at the 5% level) between the GII of the multinational's home country and its female employment share in China. In column (2), when we add a wide range of firm covariates as controls in addition to fixed effects, we find a much more statistically significant (at the 1% level) correlation between the two. Based on the estimate -0.099, a one-standard-deviation decrease in a country's GII (0.195, changing Malaysia's GII to that of Germany; see Table 2) is associated with about 1.9 percentage-points higher female employment share. We find no evidence that home countries' incomes affect their foreign affiliates' female shares. Firms' computer intensity, R&D intensity, and TFP are all negatively correlated with their female employment shares. In other words, our results show that among FIEs, technology does not appear to complement firms' female employment.[20] The positive coefficient on firm age implies that older FIEs hire proportionately more women, rejecting the assimilation hypothesis in this context. In column (3) we use an alternative measure of country gender norms – World Value Survey score – as an independent variable. The positive and statistically significant correlation (recall that a higher WVS score implies a more positive attitude towards women) is consistent with the findings in column (1) and (2).

In columns (4) and (5), we use female employment share in low-skilled and skilled employment as the dependent variable, respectively, to investigate potentially different effects for the two groups. We find that while for both skill groups, a higher home country's GII is associated with a lower

communication and management skills, then we should expect a positive correlation between a firm's size and its female employment share, something that our regression results confirm.

[20] There may still be a difference in technology between domestic and foreign firms, which could explain the difference in their female employment shares. However, since we aim identify cultural transfer by exploiting the cross-country differences in culture, such a comparison is not possible in this context.

female employment share, a larger relationship is found for the low-skilled workforce in a firm. We also find that a higher skill intensity of production is associated with a higher female employment share, while it is negatively correlated with the share of female workers in low-skilled employment. This may explain why skill intensity is not statistically significant when both skilled and low-skilled workers are mixed together in column (1).[21] Column (6) uses the dummy for whether the FIE has a female manager as the dependent variable. We find a negative and significant correlation between GII and the probability, suggesting that FDI cultural transfer affects not only employment of female workers, but also the appointment of females at the management level of the firm.

An alternative hypothesis for why foreign firms hire more women than domestic firms is because of their intention to exploit the low wages of a group of workers, who are discriminated in the labor markets (Siegel, Kodama, and Halaburda, 2014). In Table A4 in the appendix, we use China's urban household survey data for 2004-2007 and find that the prevalence of FDI in a city is related to lower wage premium for men. While these results do not suggest causal relationship, they do confirm that foreign firms do not seem to be attracted to markets where female wages were lower, or that their presence depressed female wages further.

2.2.2 Evidence on Cross-Border Cultural Spillover to Domestic Firms

In this section we examine whether gender cultural transfer will spillover to domestic Chinese firms. Again, we use the firm's female share in total employment and the dummy for whether it has a female manager/ CEO as the main dependent variables. We adopt the empirical specification widely used in the literature on FDI and technology spillover (e.g., Aitken and Harrison, 1997; Javorcik, 2004) to explore cross-sectional correlation between the prevalence of FDI and the outcome variables of interest of domestic firms in the same market. We take advantage of the detailed industry and geographic information of our firm data and define a market (k) as either a narrowly defined industry or city (345). The main specification for estimating cultural spillover is

$$\left(\frac{f}{f+m}\right)_{ik} = \gamma_0 + \gamma_1 FDI_k + \mathbf{X}'_{ik}\boldsymbol{\gamma} + \{FE\} + \varepsilon_{ik}, \tag{3}$$

where $\left(\frac{f}{f+m}\right)_{ik}$ is the female share in employment or an indicator for a female manager of firm i in market k. FDI_k is the share of FIEs in total sales in market (industry or city) k. The results based on FIEs' share of employment in the same industry are reported in the appendix. $\mathbf{X}_{ik}$ is the

[21] In unreported results, we also find that the spillover effects are stronger for wholly-owned FIEs compared to joint ventures. To the extent that larger equity ownership by the multinational headquarters implies more control, the finding of a larger transfer associated with wholly-owned FIEs is consistent with our hypothesis that culture is transferred from the top, instead of from below as would be observed if FIE adapt to local culture.

vector of the same firm characteristics included in eq. (2). $\{FE\}$ includes a host of fixed effects.

We control for the ratio of imports to total sales in industry k to capture the possibility that import competition, as shown by Black and Brainerd (2004), may reduce gender inequality due to increased competition. According to the classic work by Becker (1957), increased competition drives firms to discriminate less, or else they will be forced to exit. For the same reason, we also include a Herfindahl index of the industry to control for changes in the degree of competition, possibly due to an increased prevalence of FIEs. By controlling for the change in the industry's degree of competition, any remaining effect of FDI should be due to cultural or technology spillover. As often emphasized by the FDI literature, local firms learn from FIEs about product designs, production technology, or even corporate culture. All these can be gender-biased. It is possible that technology upgrading increases the demand for female labor, as in the case in Mexico highlighted by Black and Brainerd (2004). Since FDI is often associated with technology transfer to local firms, such transfer or imitation could affect domestic Chinese firms' employment shares by gender. To partially control for this technology-induced changes in employment structure, we control for a host of measures of domestic firm's technology, as included in Table 3.

We estimate eq. (3) using a sample that includes only domestic Chinese firms but excludes all FIEs. We first report the results when a market is defined as a 4-digit industry in Table 4, followed by the results reported in Table 5 for regressions with markets defined as one of 345 cities. Column (1) of Table 4 shows that the FIEs' share of output is positively correlated with the share of female in domestic firms across narrowly defined industries, controlling for province fixed effects. In column (2), we use the female dummy for the manager of a domestic firm as the dependent variable. Based on the cross-section data for 2004, we find a positive correlation between the FDI prevalence and the probability that the manager of a domestic firm is a female.[22] In particular, controlling for sector fixed effects and a host of firm covariates that can affect the probability of appointing a female manager, such as skill intensity, we find that a one standard deviation increase in the FIEs' share in an industry's output (0.218) is associated with about one percentage-point increase in the likelihood that a female manager is appointed by a domestic firm. Interestingly, we find negative coefficients on both the industry's Herfindahl index and import share. The negative coefficient on the Herfindahl index is consistent with Becker's (1957) hypothesis that competition should reduce discrimination. The negative correlation between import share and domestic firms' female-male employment ratio, however, cannot be explained by the same hypothesis.

One may be concerned that FIEs self-select into industries in which females have a comparative

[22] Since there is infrequent change in the manager (legal representative) of a firm between 2004-2007, we do not have enough variation to identify the potential positive correlation using the panel data and control for firm fixed effects.

advantage, and thus, the positive correlation observed across industries may well be a result of selection. To address this concern, from columns (3) to (5), we use the 2004-2007 panel data, which allows for the control of firm or industry fixed effects. Within a firm and controlling for year fixed effects, foreign output share is positively correlated with the female employment share among domestic firms across industries. The correlation is economically significant – a one standard deviation increase in the share of an industry's output (0.218; see Table 2) is associated with an average 0.7 percentage-point increase in the share of female workers in a domestic firm in the same industry.

In columns (4) to (5), we use the share of female workers of a domestic firm as the dependent variable to examine whether FDI from countries with lower gender inequality is associated with a larger spillover. Specifically, in addition to the stand-alone measure of FDI prevalence in the sector, we include an interaction term between the FDI prevalence and the country of origin's index of gender gaps, measured either by the average of GII or the WVS score. Controlling for firm and year fixed effects, column (4) shows not only a positive and significant coefficient on the prevalence of FDI, but also a negative and significant coefficient on the interaction term. Column (5) shows a positive coefficient on the interaction between the measure of FDI prevalence and WVS score, supporting the findings in column (4). In other words, the cultural spillover from FIEs documented so far appear to be coming from those that are from countries with culture that is more favorable for women.

In Table 5, we report the estimation results about the correlation between the prevalence of FDI and domestic firms' female employment shares across cities. Similar to the results at the industry level reported in Table 4 and Table A7 in the appendix, we find that the prevalence in FDI in a city (measured by output share or employment share) is positively correlated with domestic firms' employment of women and appointment of female managers. These results are obtained after controlling for firm fixed effects, and industry-level import shares and Herfindahl indices.

3 Model

After documenting evidence of cultural transfer and spillover from foreign firms, the next step is to quantitatively analyze the productivity loss due to gender inequality, the mechanism of cultural spillover, and its associated productivity gains. To this end, we build a parsimonious multi-sector task-based model that features firm heterogeneity in productivity and biases towards female workers, as well as women having a comparative advantage in skill- versus physically-intensive (brawn) tasks. We outline the main features of the model in the main text, relegating the technical details

and proofs to the appendix.

3.1 Set-up

3.1.1 Environment

Our model analyzes an economy with a three-layer structure: sectors, firms, and tasks. The economy is endowed with M male workers and F female workers, who have identical preferences. Consumers consume goods, based on Cobb-Douglas utility, from a continuum of sectors, indexed by $j \in [0,1]$. To be discussed later, j also indicates female comparative advantage of the sector. Within a sector (j), consumers have Dixit-Stiglitz preferences with elasticity of substitution between varieties equal to $1/\left(1-\eta_j\right) > 1$. Within each sector, heterogeneous firms pay entry cost to enter each sector. Upon entry, a firm produces and sell horizontally differentiated varieties in monopolistically competitive markets.

The market structure together with Dixit-Stiglitz preferences imply that each firm (i) is facing demand $y_i = A_j p_i^{-\frac{1}{1-\eta_j}}$, where A_j is a sector-j specific demand factor and p_i is the price charged by firm i.

3.1.2 Production

On the supply side, the micro-foundation of the model is built on Acemoglu and Autor (2011) (AA hereafter). Each firm hires a continuum of tasks. Tasks are combined based on a CES production function that differs across sectors. The appendix shows that production functions micro-founded on tasks with varying skill intensities can ultimately be expressed as one that features constant elasticity of substitution between female and male labor inputs. Specifically, the production function of firm i in sector j is

$$y_{ij}\left(\varphi_i\right) = \varphi_i \left[\beta_j^{\frac{1}{\kappa_j}} f_{ij}^{\frac{\kappa_j-1}{\kappa_j}} + \left(1-\beta_j\right)^{\frac{1}{\kappa_j}} m_{ij}^{\frac{\kappa_j-1}{\kappa_j}}\right]^{\frac{\kappa_j}{\kappa_j-1}},$$

where φ_i is firm i's total factor productivity. f_{ij} and m_{ij} are the firm's female and male employment in sector j. $\kappa_j \in [1,\infty)$ is the elasticity of substitution between female and male labor inputs.[23] β_j represents the importance of skill inputs relative to brawn inputs in sector j. Since we will focus on a firm's problem, let us suppress both firm (i) and sector subscripts (j) from now on until the discussion of the cross-industry pattern of spillover.

[23] A CES production function with female and male labor inputs being gross substitutes have also been assumed by Olivetti and Petrongolo (2014) who study the relationships between gender wage gaps and structural change in an economy.

Firms are heterogeneous in productivity, as in Melitz (2003). In this model, they are also different in terms of the degree of statistical discrimination. Following the literature on statistical discrimination (Phelps, 1972 and Arrow, 1973) and subsequent studies (see the summary by Fang and Morro, 2010), we model discrimination as an outcome due to information asymmetry about workers' productivity. Notice that taste-based discrimination is considered in our model once we assume that a firm's prior expected productivity of workers deviates from the truth. In general, what is crucial is that local firms are either uninformed or prejudiced towards women, due to distorted belief that prevails in society (Alesina, Giuliano, and Nunn, 2013).

Let γ be a firm's perceived relative labor productivity of female workers. If a firm has $\gamma < 1$ and the truth is that female and male workers have the same average productivity, then there is taste-based discrimination. We assume that before entering the market, a firm draws productivity φ from a cumulative distribution function $G(\varphi)$ over $[0, \infty)$, as well as the perceived productivity for female workers (γ). Both φ and γ are assumed to be independently distributed from each other. A firm with the parameter bundle (φ, γ) selling goods in a particular sector has revenue equal to $R(\varphi, \gamma) = A^{1-\eta} y(\varphi, \gamma)^{\eta}$, where A determines the level of demand in the sector, which is taken as given by each firm. $y(\varphi, \gamma)$ is the firm's output level, which depends on both productivity and its perceived productivity of female workers. While $\frac{\partial R(\varphi,\gamma)}{\partial \varphi} > 0$, the relation between $R(\varphi, \gamma)$ and γ can be non-monotonic, as any biases against certain group of workers would lead to a deviation from the optimal employment mix. This will be further elaborated below.

3.1.3 Labor Supply

Labor is differentiated by gender. Female and male workers are each endowed with a different combination of skills and brawn. Consistent with the literature and empirical evidence, we assume that relative to male workers, female workers are endowed with more skills than brawn and thus have a comparative advantage in skill-intensive tasks (e.g. Pitt et al., 2012, Alesina, Giuliano, and Nunn, 2013).[24] As in AA, each worker has one unit of time and has to decide how to allocate the time to supply brawn or skills. In the appendix, we show that the no-arbitrage wage condition will imply that female workers will allocate all their time to supply skills, while male workers will only supply brawn. The idea is that wages will adjust to reflect workers' comparative advantage, in the same fashion prices adjust to reflect countries' comparative advantage in the standard Ricardian trade model. In equilibrium, both female and male workers will therefore completely specialize in what they are relatively better at. In the appendix, we show that this one-to-one mapping between

[24] Obviously this strong result depends on the simplifying assumption that all men have the same comparative advantage in brain and skills. A richer setup involves different distributions of comparative advantage between men and women, with the former group have a higher mean of relative endowment brawn versus skills.

gender of the workers and task supply turns the firm's problem of choosing tasks into one that maximizes firm profit based on a constant elasticity of substitution production (CES) function of male and female labor workers.

3.1.4 Firm Equilibrium

In this section, we solve for the firm equilibrium in a sector. In particular, we analyze how heterogeneous firm productivity and information-based (statistical) discrimination affect firms' employment choices and profits (Phelps, 1972 and Arrow, 1973).[25]

We assume that the perception of a firm about female and male labor productivity depends on its country of origin. The idea that information or perception are shaped by the country's social norms is similar to the rule-of-thumb judgement of certain groups of people's productivity discussed by Alesina, Giuliano, and Nunn (2013). Specifically, let us normalize the true productivity of male and female workers to both equal to 1. Firms hold prior beliefs that the relative productivity of female workers γ is distributed log-normally with mean μ and variance ν: $\log \gamma \sim N(\mu, \nu)$. A common bias against women in society is captured by the following assumption:

Assumption 1: $\mu < 0$ and $\nu > 0$.

We will make both μ and ν country-specific in the next section about cultural spillover. In addition to drawing γ, the firm draws its total factor productivity φ from a cumulative distribution function $G(\varphi)$ as in Melitz (2003). φ is assumed to be firm-specific, time-invariant, and is not subject to learning or spillover from FDI.

We assume that the firm sets labor demand before uncertainty is unveiled. Based on the realized output, prices are going to adjust ex post to make sure that firm supply equals demand for its goods. The firm chooses its labor demand by solving the following profit maximization problem.

$$\pi(\varphi, \gamma) = \max_{f,m} \{A^{1-\eta} y_e(\varphi, \gamma, f, m)^{\eta} - w_f f - w_m m - \phi\}, \tag{4}$$

where

$$y_e(\gamma, f, m) = \varphi \left[(\gamma\beta)^{\frac{1}{\kappa}} (f)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m^{\frac{\kappa-1}{\kappa}} \right]^{\frac{\kappa}{\kappa-1}}, \tag{5}$$

where the subscript 'e' represents the expected output by hiring female and male workers. ϕ is the fixed cost measured in final goods.

[25] In the empirical analysis below, we will provide evidence to show the relative importance of taste-based discrimination, as proposed by Becker (1962).

Solving the problem yields

$$f(\varphi,\gamma) = (\beta\gamma)\,\widetilde{A}\widetilde{\varphi}\frac{c(\gamma)^{\kappa-\frac{1}{1-\eta}}}{w_f^{\kappa}}; \tag{6}$$

$$m(\varphi,\gamma) = (1-\beta)\,\widetilde{A}\widetilde{\varphi}\frac{c(\gamma)^{\kappa-\frac{1}{1-\eta}}}{w_m^{\kappa}}, \tag{7}$$

where

$$c(\gamma) = \left[(\gamma\beta)\,w_f^{1-\kappa} + (1-\beta)w_m^{1-\kappa}\right]^{\frac{1}{1-\kappa}} \text{ with } c'(\gamma) < 0; \tag{8}$$

and $\widetilde{\varphi} = \varphi^{\frac{\eta}{1-\eta}}$; $\widetilde{A} = A\eta^{\frac{1}{1-\eta}}$.

Dividing (6) by (7) yields an expression for $\frac{f}{m}$ that depends on the firm's perceived γ:

$$\frac{f}{m} = \gamma\left(\frac{\beta}{1-\beta}\right)\left(\frac{w_f}{w_m}\right)^{-\kappa}. \tag{9}$$

It is clear that all else equal, a firm's $\frac{f}{m}$ is increasing in the perceived female labor productivity (γ) and the sector's female comparative advantage (β), but decreasing in $\frac{w_f}{w_m}$.

Under the assumption of identical productivity between female and male workers, the optimal female-male employment ratio is obtained when $\gamma = 1$, implying $\left(\frac{f}{m}\right)^* = \frac{\beta}{1-\beta}\left(\frac{w_m}{w_f}\right)^{\kappa}$. A firm's perceived labor productivity can be biased in either direction. When $\gamma > 1$, a firm chooses $\frac{f}{m}$ larger than the optimal ratio. Consider two FIEs' countries of origin (c and c'), with country c having a more pro-women culture represented by $\mu_c > \mu_{c'}$ and $\nu_c < \nu_{c'}$. We should expect that a firm from c, due to a higher probability of drawing a higher γ, has a higher $\frac{f}{m}$. This prediction is consistent with the main empirical results reported in Table 3 – foreign firms from countries with a higher gender inequality tend to employ fewer women in their foreign affiliates in China. For completeness, let us summarize this set of theoretical results as follows.

Proposition 1 *Firms from countries that hold a more biased view towards female labor productivity (i.e., a lower γ) have a lower average female-to-male employment ratio within an industry. The relationship is quantitatively stronger in sectors in which female comparative advantage is larger (higher β).*

3.1.5 The Effects on Firm Profit

How does a biased belief about female labor productivity affect the firm's actual profit and measured productivity? To answer this question, let us turn to the firm's outcomes based on the firm's ex ante employment decisions but the actual productivity of the workers.

Substituting $f(\varphi,\gamma)$ and $m(\varphi,\gamma)$ from (6) and (7), respectively into the realized output function, $y^r(f,m) \equiv y^e(1,f,m) = \varphi\left[\beta^{\frac{1}{\kappa}}(f)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}$ yields the actual output level of the firm with φ and γ

$$y_r(\varphi,\gamma) = \widetilde{A}\widetilde{\varphi}c(\gamma)^{\kappa-\frac{1}{1-\eta}}\left[\gamma^{1-\frac{1}{\kappa}}\beta w_f^{1-\kappa} + (1-\beta)w_m^{1-\kappa}\right]^{\frac{\kappa}{\kappa-1}}.$$

Not surprising, $\frac{\partial y}{\partial \gamma} > 0$.[26] It is more important to check the effect of a biased γ on profit, which takes the form:

$$\begin{aligned} \pi(\varphi,\gamma) &= A^{1-\eta}y_r(\varphi,\gamma)^{\eta} - w_f f(\varphi,\gamma) - w_m m(\varphi,\gamma) - \phi \\ &= \widetilde{A}\widetilde{\varphi}c(\gamma)^{-\frac{\eta}{1-\eta}}\left[\frac{1}{\eta}B(\gamma)^{\frac{\eta\kappa}{\kappa-1}} - 1\right] - \phi \end{aligned} \tag{10}$$

where

$$c(\gamma) = \left[(\gamma\beta)\, w_f^{1-\kappa} + (1-\beta)w_m^{1-\kappa}\right]^{\frac{1}{1-\kappa}} \text{ with } c'(\gamma) < 0; \tag{11}$$

$$B(\gamma) = \frac{\gamma^{-\frac{1}{\kappa}}\beta\gamma w_f^{1-\kappa} + (1-\beta)w_m^{1-\kappa}}{\beta\gamma w_f^{1-\kappa} + (1-\beta)\, w_m^{1-\kappa}}, \tag{12}$$

which is decreasing in γ.[27] Since $c'(\gamma) < 0$, $\frac{\partial \pi(\varphi,\gamma)}{\partial \gamma}$ is not monotonic. In fact, basic intuition tells us that $\pi(\varphi,\gamma)$ is maximized when expected γ is exactly equal to the actual value (i.e., 1). Any expected value that is either larger or smaller than 1 will lower $\pi(\varphi,\gamma)$. As such, as proved in the appendix, $\frac{\partial \pi(\varphi,\gamma)}{\partial \gamma} > 0$ for $\gamma < 1$ and $\frac{\partial \pi(\varphi,\gamma)}{\partial \gamma} > 1$.

Notice that the negative relationship between the bias and firm profits differ across sectors, as can be shown by $\frac{\partial \ln \pi(\varphi,\gamma)}{\partial \gamma \partial \beta} < 0$. Intuitively, sectors that are more skill-intensive, or female-dependent, will suffer from a larger loss due to discrimination. We summarize the results in this section in the following proposition, which will be tested in Section 4.

Proposition 2 *All else being equal, firms that are more biased against women have lower profits, especially in sectors in which female comparative advantage is larger.*

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[26] Notice that when $\gamma = 1$, $y = \widetilde{A}\varphi^{1+\left(\frac{1}{1-\eta}-\kappa\right)}\left[\beta w_f^{1-\kappa} + (1-\beta)w_m^{1-\kappa}\right]^{\frac{1}{\kappa-1}\frac{1}{1-\eta}}$.

[27] When $\gamma = 1$, the firm has the right expectation about the female labor productivity. $\pi(\varphi,1) = \widetilde{A}\widetilde{\varphi}c(\gamma)^{-\frac{\eta}{1-\eta}}\left[\frac{1}{\eta}B(1)^{\frac{\eta\kappa}{\kappa-1}} - 1\right] = \widetilde{A}\widetilde{\varphi}\,(1-\eta)\,c(1)^{-\frac{\eta}{1-\eta}}$, the familiar form.

Biased belief and the resulting suboptimal choices of female (and male) workers will also affect the firm's revenue-based total factor productivity ($TFPR$). According to Hsieh and Klenow (2009) and subsequent studies on misallocation of resource, an industry's physical TFP is negatively related to the dispersion of firms' $TFPR$ in the industry. Through the lens of the models of misallocation, we will study the cost (in terms of productivity) of gender discrimination in China in Section 5. Before we do that, let us formalize the process of cultural spillover from foreign firms, as a learning processing.

3.2 Cultural Spillover

Besides cultural transfer, an interesting question to ask is whether multinational affiliates induce local firms to hire more women? In other words, is there cultural spillover from FDI in addition to technology spillover that has been well documented in the literature? There are two potential channels through which local firms may respond to FDI, namely competition and imitation. Regarding competition, the entry of foreign firms into a market may drive up input costs and increase goods-market competition. Both effects lower profits for all, possibly inducing firms to hire more women. This is particularly true for the least productive firms who are concerned about survival. The competition channel is not new and in fact was originally proposed by Becker (1957), which has been verified by subsequent empirical studies (e.g., Black and Brainerd, 2004).

In addition, domestic firms, by interacting with FIEs in the same market, will update their beliefs about female labor productivity over time. The updating will be towards the true level of ($\gamma = 1$) if FIEs are from countries that hold a less biased view about female labor productivity. Now let us introduce the information structure to analyze how information spillover to domestic firms, which in turn affect their female employment. From the previous section, we specify that a firm forms prior belief about female labor productivity based on $\log \gamma \sim N(\mu, \nu)$. Following the literature on statistical discrimination (Fang and Moro, 2010), we assume that firms from countries that are more biased against women are less certain about their productivity (i.e., higher ν). Moreover, following the seminal paper by Phelps (1972), we assume that firms from those countries perceive a lower average female labor productivity (i.e., a lower μ). We can rewrite a firm's prior belief as the following equations:

$$\gamma = \mu + \varepsilon,$$

where ε is an error of the perception, which is assumed to be distributed $N(0, \nu)$.

Assume that a firm cannot learn from itself but only from neighboring firms about γ.[28] Consider a domestic firm that observes the "signals" from n neighboring firms, who hold different priors about female labor productivity. Suppose that the firm can observe the labor productivity of female workers with noise.[29]

$$z = \mu^* + \varepsilon^* + \xi, \tag{13}$$

where μ^* is the mean of the belief about female labor productivity, held by the neighboring firms from a foreign country (denoted by $*$). ε^* is the error of the foreign firm's perceived female labor productivity, which is normally distributed with mean 0 and variance equal to ν^*. For simplicity, we do not distinguish different countries of origin of the foreign firms in the model. Furthermore, we make no assumption about whether μ^* is larger than μ or not, nor the inequality between ε^* and ε, as foreign firms in the same market (industry or city) may hold a less favorable view towards women, compared to the domestic firm. $\xi \sim N(0, \upsilon_w)$ is the observational white noise, assumed to be independently distributed from ε^*. Therefore, the error of the signals observed, from the point of view of the firm, has two components ε^* and ξ. For notational simplicity, let us define $\lambda^* = \varepsilon^* + \xi$ and rewrite (13) as

$$z = \mu^* + \lambda^*,$$

where λ^* is normally distributed with mean 0 and variance equal to $\omega = \nu^* + \nu_w$.

How does this signal help the firm to update its own prior beliefs? Based on $\overline{z}'s$ inferred from n neighbors, the firm updates its prior using Bayes's rule.[30] The posterior belief is normally distributed with the following posterior mean of μ:[31]

$$\mu^{'}(n, \overline{z}) \equiv E[\mu | n, \overline{z}] = \delta \overline{z} + (1 - \delta)\mu, \tag{14}$$

where δ is the weight the firm puts on the observed (sample) mean $\overline{z} = \frac{1}{n}\sum_{l=1}^{n} z_l$, based on observed z_l from n neighboring firms, possibly from different countries of origin. According to

[28] The assumption that a domestic firm cannot infer the true γ seems strong but imagine that a firm is also trying to solve the same model as us, observing realized output y_r and knowing f and m may not allow it to tease out the true γ. One possibility is that the firm may think a higher than expected output level is due to a higher than expected male labor productivity.

[29] The assumption that the firm observes its neighbors' female labor productivity seems strong. Alternatively, we can make a more intuitive assumption that the firm observes its neighboring firms' female-male employment ratio. The firm can then infer at least the *relative* labor productivity of neighboring firm j: $\gamma = \left[\left(\frac{f}{m}\right)\frac{1-\beta}{\beta}\left(\frac{w_f}{w_m}\right)^{\kappa}\right]^{\frac{1}{\kappa-1}}$.

[30] See the seminal book by Degroot (2004) for a derivation.

[31] See Chapter 9 of DeGroot (2004).

Degroot (2004), δ can be derived as

$$\delta(n, v, \omega) = \frac{nv}{\omega + nv} = \left(1 + \frac{1}{n}\frac{\omega}{v}\right)^{-1}. \tag{15}$$

Partial differentiation yields the following comparative statics regarding the relationship between the number of neighbors, the precision of the prior, and the precision of the signal (summarized from observed neighbors' employment shares):

$$\begin{aligned} \frac{\partial \mu'}{\partial n} &= \frac{\partial \mu'}{\partial \delta}\frac{\partial \delta}{\partial n} > 0; \\ \frac{\partial \mu'}{\partial (\omega/v)} &= \frac{\partial \mu'}{\partial \delta}\frac{\partial \delta}{\partial (\omega/v)} < 0; \\ \frac{\partial^2 \mu'}{\partial \overline{z} \partial n} &= \frac{\partial \delta}{\partial n} > 0. \end{aligned} \tag{16}$$

In words, when updating the prior, a firm will put a larger weight δ on other firms' signals about female labor productivity and a smaller weight on its own prior belief, (1) if there are more firms in the same market revealing the signal or (2) if the signal from other firms in the same market is less precise (higher ω keeping v constant).[32] Furthermore, there is a cross-partial between $\overline{z}$ and n. While information updating is stronger if there are more firms showing the closer-to-truth productivity of female workers, if the biases held by those observed firms are smaller (high $\overline{z}$), the positive correlation between the number of firms observed and learning will be even larger. We summarize all these comparative static results in the following proposition.

Proposition 3 *Domestic firms' shares of female employment are increasing in the prevalence of FDI in the same sector or city. For the same level of FDI, the spillover will be stronger if the gender gap between domestic firms and foreign firms is larger (higher $\overline{z}$), while it will be weaker if the observed signal about female productivity is less precise (higher ω).*

The posterior variance of γ', given n, v, and ω, can be expressed as

$$v'(n, v, \omega) = \frac{\omega v}{\omega + nv} = \left(\frac{1}{v} + \frac{n}{\omega}\right)^{-1}, \tag{17}$$

[32] The firm will also put a larger weight on the signal if it is less informed about the labor productivity of a particular gender, in the case of China and many developing countries, that would be the labor productivity of female workers. In empirical analysis, we plan to explore the correlation between ω_g/v_g and female employment shares across cities or industries, without distinguishing whether it is due to low ω_g or high v_g that the firm updates its prior more.

and has the following properties:

$$\frac{\partial v'}{\partial n} < 0; \frac{\partial v'}{\partial v} > 0; \frac{\partial v'}{\partial \omega} > 0.$$

The precision of the posterior, $1/v'$, increases with the number of neighbors revealing the signal. If either the precision of the signal or the precision of the prior belief is low, the posterior belief will also be less precise.

To sum up, the way that we model cultural transfer and spillover are as follows. Compared to domestic firms, we assume that foreign firms perceive a higher mean productivity of female workers (i.e., $\mu^* > \mu$) and are also more informative about their own productivity (i.e., $v^* < v$). As such, they are more likely to employ proportionately more women than domestic firms. This point is intuitive and was already validated empirically in Tables 4 and 5 above. The presence of foreign firms in the same market, which presumably have a higher female employment share than domestic firms, permits the latter to learn about a more profitable female-male employment ratio. Such social learning exhibits itself as a change in social norm in society, and thus can be interpreted as cultural spillover.

If we go back to eq (9) about the firm's female-to-male ratio, we can show that information updating (learning) is larger in sectors in which women have a comparative advantage, as

$$\begin{aligned} \frac{\partial}{\partial \beta} \frac{\partial \left(\frac{f}{m}\right)}{\partial n} &> 0 \\ \frac{\partial}{\partial \beta} \frac{\partial^2 \left(\frac{f}{m}\right)}{\partial \overline{z} \partial n} &> 0 \end{aligned}$$

The idea is that the benefit (the cost) of updating (discrimination) is larger in sectors in which female workers have a stronger comparative advantage.

Proposition 4 *The cultural spillover is stronger in sectors in which female comparative advantage is larger.*

4 Empirical Examination of the Model Predictions

4.1 Female Employment Share and Firm Profits

To investigate the relationship between firm profit and its gender inequality, as predicted by Proposition 2, we regress a firms' ratio of profits to sales as the dependent variable on its female em-

ployment share and other control variables, using the 2004-2007 panel data.[33] Table 6 reports the estimation results. Controlling for firm and year fixed effects, column (1) shows a positive and statistically significant correlation between a firm's female share and its profit margin. We repeat the same analysis using the subsamples of domestic firms and foreign firms in columns (2) and (3), respectively. Importantly, the correlation between the female employment share and profits is only observed for domestic firms but not for foreign firms. These results indirectly suggest that discrimination is widespread and is more costly for domestic firms. Increasing the female employment is associated with a higher profitability for the same firm.

In columns (4)-(6) we repeat the same analyses by including also variables for firm's R&D intensity, capital intensity, (log) wage rate, (log) firm age, and (log) employment (i.e., the same set of firm controls that we included in the previous tables).[34] The positive correlation between firm female employment share and profits remains robust.

4.2 Examining the Channels of Cultural Spillover

Table 7 examines whether the spillover effect differs across industries, countries of origin, and firms with heterogeneous productivity, using the 2004-2007 firm panel data. In column (1), we add an interaction term between the prevalence of FDI (FDI hereafter) and the sector measure of female comparative advantage. The measures of female comparative advantage are from Do, Levchenko and Raddatz (2014), who compute the female share in employment in each industry using the United Nations Industrial Development Organization (UNIDO) data from a wide range of countries. The sectors with the highest female employment share include wearing apparel, footwear and caps; textile; as well as leather, fur, feather, and relate products. The sectors with the highest male employment share include ferrous and non-ferrous metals; petroleum, coking, processing of nuclear fuel; as well as transport equipment. See Table A5 for the sectoral ranking of female comparative advantage).[35] We find that the cultural spillover is stronger in sectors in which women have a comparative advantage. When we include a triple interaction term between FDI, the average GII of FIEs in the industry, and the measure of female comparative advantage, we find that not only the spillover is stronger from high-GII FIEs, it is particularly stronger in sectors in which women's comparative advantage is higher. In summary, we find evidence for Proposition 4 that the

[33] We use the firm's profit-sales ratio rather than log(profit) as the dependent variable as there are many negative values for profits in the data.

[34] We replace ln(output) by ln(employment) for this analysis as obviously, revenue and output are strongly correlated. As the goal is to control for the scale effect on profits (and female employment shares in previous tables), using ln(employment) is a compromising alternative. Importantly, all results in this table remain quantitatively similar. The t-statistics of ln(output), if included, is very high. Results are available upon request.

[35] The gender comparative advantage measures are available at the ISIC level. We created a concordance table to match each ISIC code to multiple Chinese 4-digit industry codes.

spillover effect is stronger in sectors in which female comparative advantage is larger. Going back to Table 3 where we examine cultural transfer from the headquarter to foreign affiliates, we also find stronger cultural transfer within multinational firms' boundary (see column (7)). This result supports Proposition 1.

Columns (3) and (4) examine whether spillover is stronger in the more competitive markets. In addition to the standalone FDI variable, we include an interaction between FDI and the Herfindahl index of the industry, as well as a triple interaction between FDI, the Herfindahl index, and the GII of the FIEs' countries of origin. Both coefficients are negative and significant, suggesting that the cultural spillover is stronger in the more competitive industries (those that have lower Herfindahl indices). Related to this finding, in column (5), we find that the spillover effect is stronger for the less productive domestic firms (in terms of measured TFP). The coefficient on the interaction between GII, FDI and (log) TFP of the domestic firm (reported in column (6)) has the expected sign but is however insignificant.

Next, we take the model seriously and examine whether cultural spillover (or learning) is weaker if the signals about female labor productivity from foreign firms are more dispersed. To this end, in columns (7) and (8), in addition to the FDI standalone variable, we include interaction terms between FDI and the standard deviation of the GII across the FIEs in the same industry. The signs of the coefficients on the interactions are consistent with our theoretical prediction that learning is weaker if the signals are more dispersed, but the correlation is not statistically significant.

4.3 Cultural Spillover and Firm Exits

Proposition 1 states that a more discriminating (biased) firm has a more distorted female-male employment mix, thus having a lower profit. Although we do not explicitly study entry and exit in the model for simplicity, it is natural to postulate that increased competition, due to a higher share of possibly more efficient (and less discriminating) foreign firms in a market, will force the more discriminating and less profitable firms to exit the market. In other words, despite our theoretical focus on statistical discrimination, our model delivers results that resonate with the predictions by the models on taste-based discrimination (a la Becker, 1957).

To study how Becker's hypothesis more formally, we regress a domestic firm's dummy for exiting a market in the next year on the output share of foreign firms in the same industry, the firm's female employment share, and the interaction of the two, controlling for the same set of firm controls that we have included in previous regressions, along with industry and year fixed effects. Table 8 reports the estimates based on a linear probability model. In column (1), we find a negative and significant coefficient on the share of female workers in the firm, suggesting that

firms with more female workers are more likely to survive on average.[36] However, in contrast to our expectation, the coefficient on the interaction term between the firm's female employment share and FDI is positive. When we include the interaction between $FDI\times$female share and the home country's GII in column (2), or include the interaction between $FDI\times$female share and the sector measure of female comparative advantage in column (3), we find a stronger negative correlation between firm exit rates and female employment when (i) the market pressure is from foreign firms whose home countries' culture is more pro women, or (ii) in sectors in which women have a stronger comparative advantage. In sum, our regression results, together with those from columns (5) to (8) in Table 7, largely confirm Becker's hypothesis that competition is an important reason for why firms may become less discriminating again certain groups of workers. That said, the finding that spillover from the more pro-women FDI source countries is stronger suggests that the cultural effect of FDI is above and beyond competition. Information is important too.

5 Quantifying the Effects on Aggregate TFP

In this section, we use the model developed in Section 3 to quantify the productivity loss due to gender discrimination and the productivity gain from cross-country cultural spillover.

5.1 Quantifying the Productivity Loss due to Gender Discrimination

Based on the model, we first derive a firm's physical TFP ($TFPQ$) and revenue TFP ($TFPR$). The marginal revenue product for female and male workers can be derived as (see the appendix for detailed derivation):

$$MRP_f = B(\gamma)^{-\frac{\kappa(1-\eta)-1}{\kappa-1}} \gamma^{\frac{-1}{\kappa}} w_f \tag{18}$$

$$MRP_m = B(\gamma)^{-\frac{\kappa(1-\eta)-1}{\kappa-1}} w_m \tag{19}$$

As shown in the appendix, both MRP are decreasing in γ. The revenue total factor productivity ($TFPR$) of the firm, defined as revenue divided by the input aggregate, can be expressed as

$$TFPR\,(\varphi, \gamma) = \eta^{-1} c(\gamma) B(\gamma)^{-\frac{(1-\eta)\kappa}{\kappa-1}} \tag{20}$$

[36] Recall that we already control for a host of firm-level controls, including firm productivity. So this result is unlikely to be related to any observed superior performance of female-intensive firms, alleviating partially the concern of simultaneity bias.

where $c(\gamma)$ and $B(\gamma)$ are defined above. In the appendix, we show that $TFPR$ is decreasing in γ. In other words, a more positive view towards female labor productivity is associated with a *lower* firm revenue TFP. While it sounds counterintuitive, it is actually consistent with the findings of a positive relationship between the firm's tax rate and $TFPR$ in Hsieh and Klenow (2009). The rationale is that in a model that features constant markups over marginal costs, a higher firm's $TFPR$ does not indicate higher efficiency. On the contrary, higher prices (or lower quantity supplied) by the less efficient firms result in higher (measured) $TFPR$. In other words, two firms with the same intrinsic physical productivity, because of biases and thus suboptimal employment decisions, have different $TFPR$. Our model proposes that it arises from discrimination, although in reality, there can be many different sources of distortion that deliver similar results, such as differences in treatments by the government or market power (the variable markup story).

According to Hsieh and Klenow (2009) and subsequent studies on misallocation of resource, an industry's physical TFP is negatively related to the dispersion of firms' $TFPR$ in the industry. Through the lens of the models of misallocation, we will study the cost (in terms of productivity) of gender discrimination in China. Specifically, according to Hsieh and Klenow (2009), an industry's $\ln TFP$ can be expressed as:

$$\ln TFP_j = \frac{1}{M_j}\left(\sum \ln TFPQ_{ij}\right) + \frac{\eta}{2(1-\eta)}\left[var\left(\ln TFPQ_{ij}\right) - var\left(\ln TFPR_{ij}\right) - 2cov\left(\ln TFPQ_{ij}, \ln TFPR_{ij}\right)\right] \tag{21}$$

Based on the structure of our model, we can compute each firm's $TFPR$ and $TFPQ$ (physical TFP which in theory should be equal to φ in the model) as

$$TFPR = \frac{R(\varphi,\gamma)}{\left[\beta^{\frac{1}{\kappa}} f(\varphi,\gamma)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m(\varphi,\gamma)^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}} \tag{22}$$

$$TFPQ = \frac{\left[R(\varphi,\gamma)\right]^{\frac{1}{\eta}}}{\left[\beta^{\frac{1}{\kappa}} f(\varphi,\gamma)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m(\varphi,\gamma)^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}} \tag{23}$$

*[*** Work in Progress ***]*

Using $\eta = 1 - \frac{1}{\sigma} = \frac{2}{3}$ from Hsieh and Klenow (2009); various β's from Do, Levchenko, and Raddatz (2014); and $\kappa = 2.5$ from Olivetti and Petrongolo (2014), we compute each firm's $TFPR$ and $TFPQ$, and then $\ln TFP_j$ for industry j based on (21).

Recall that $\frac{f}{m} = \gamma\left(\frac{\beta}{1-\beta}\right)\left(\frac{w_f}{w_m}\right)^{-\kappa}$, so we can compute each firm's discrimination factor (internal distortion) as

$$\gamma = \frac{f}{m}\left(\frac{1-\beta}{\beta}\right)\left(\frac{w_f}{w_m}\right)^{\kappa}.$$

Rewriting (20) *gives*

$$\ln TFPR \propto \frac{(1-\eta)\,\kappa - 1}{\kappa - 1} \ln\left(\frac{f}{m} + \frac{w_m}{w_f}\right) - \frac{(1-\eta)\,\kappa}{\kappa - 1} \ln\left[\frac{f}{m}\left(\frac{f}{m}\right)^{-\frac{1}{\kappa}}\left(\frac{\beta}{1-\beta}\right)^{\frac{1}{\kappa}} + 1\right].$$

Incorporating capital into the model will further permit us to compute the relative size of distortion due to gender discrimination (we don't expect it to be huge but let's see). Preliminary evidence is promising. Figure 5 shows a negative relationship between the industry's lagged output share of foreign firms and the dispersion of $\ln(1+\gamma)$ *among domestic firms, suggesting that foreign firms induce domestic firms to behave more similarly in terms of their female employment practices.*

Obviously, to gauge the potential contribution of discrimination to resource misallocation, we need to consider at least capital as another input. Suppose we have add another layer to the CES production function, by assumption that production combines capital and labor in a Cobb-Douglas sense using the production function as follows:

$$y(\gamma, f, m, k) = \varphi l\,(\gamma, f, m)^{\alpha_l}\, k^{\alpha_k} m^{1-\alpha_l-\alpha_k},$$

where

$$l\,(\gamma, f, m) = \left[\beta^{\frac{1}{\kappa}}(\gamma^{\frac{1}{\kappa-1}} f)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}},$$

the same as $y^e(\gamma, f, m)$ *as defined above.* $\alpha_l + \alpha_k + \alpha_m = 1$.

Assume that in addition to the discrimination factor, γ*, there are firm-specific capital tax and labor tax. According to Hsieh and Klenow (2009),*

$$TFPR_i \propto \frac{\widetilde{\gamma}^{\alpha_l}\,(1+\tau_{Ki})^{1-\alpha_k}}{(1-\tau_{Yi})},$$

where

$$\widetilde{\gamma} = \frac{(1-\eta)\,\kappa - 1}{\kappa - 1} \ln\left(\frac{f}{m} + \frac{w_m}{w_f}\right) - \frac{(1-\eta)\,\kappa}{\kappa - 1} \ln\left[\frac{f}{m}\left(\frac{f}{m}\right)^{-\frac{1}{\kappa}}\left(\frac{\beta}{1-\beta}\right)^{\frac{1}{\kappa}} + 1\right]$$

Each of the component can be solved as

$$
\begin{aligned}
1+\tau_{Li} &= \frac{\alpha_l}{1-\alpha_l-\alpha_k}\frac{p_m m_i}{wl_i} \\
1+\tau_{Li} &= \frac{\alpha_l}{1-\alpha_l-\alpha_k}\frac{p_m m_i}{rk_i} \\
1-\tau_{yi} &= \frac{1}{\eta}\frac{1}{1-\alpha_l-\alpha_k}\frac{p_m m_i}{R_i} \\
1+\gamma &= 1+\frac{f}{m}\left(\frac{1-\beta}{\beta}\right)\left(\frac{w_f}{w_m}\right)^{\kappa}
\end{aligned}
$$

5.2 Quantifying the Productivity Gain from Cross-Border Cultural Spillover

[to be completed]

6 Concluding Remarks

This paper studies empirically whether and how multinational firms transmit corporate culture across countries. We focus on a specific aspect of culture – social norms towards women in labor markets. Using Chinese manufacturing firm data over the period of 2004-2007, we find that foreign affiliates whose home countries' culture is more favorable for women tend to hire proportionately more women and are more likely to appoint female managers. Foreign firms, especially those from countries with a more pro-women culture, also generate cultural spillover to domestic firms, as revealed by a positive correlation between domestic firms' female employment shares and the prevalence of foreign direct investment (FDI) across industries or cities. Our estimation results are robust to the inclusion of control variables such as the home country's stage of development, firm productivity, skill intensity and R&D intensity.

To quantitatively analyze the productivity loss due to gender inequality, the mechanism of cultural spillover, and its associated productivity gains, we build a parsimonious multi-sector task-based model that features firm heterogeneity in productivity and biases towards female workers, as well as women having a comparative advantage in skill- rather than physically-intensive tasks. We then confront several model predictions using the firm data. Consistent with the model predictions, we find evidence that domestic firms respond to increased FDI by hiring more women, due to more intense competition and imitation. Such cultural spillover is stronger in sectors in which women have a comparative advantage and for the less productive firms. Quantitative analysis suggests large aggregate productivity loss due to gender inequality and potentially large productivity gains from cross-border cultural spillover.

Guided by our model, we quantify the aggregate total factor productivity loss due to discrimina-

tion against women, and how much FDI has alleviated that. Our results reveal an under-explored externality of FDI, in addition to technology spillover which has been the focus of existing studies. In sum, this paper highlights how globalization can overturn the long-run prejudice against women via economic forces, and sheds light on social policies about gender inequality.

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A Theoretical Appendix

A.1 Set-up

A.1.1 Preferences and Market Structure

The model features three layers: sectors, firms, workers (by gender) and tasks. On the demand side, there is a continuum of sectors, indexed by $j \in [0,1]$. Consumers consume these products based on a constant elasticity of substitution (CES) utility: $U = \left[\int_0^1 C_j^{\nu} dj\right]^{\frac{1}{\nu}}$, where $1/(1-\nu) > 1$ is the elasticity of substitution between products from different sectors. Within a sector, there are horizontally differentiated varieties, each produced by a firm. The consumption index for sector j, Q_j, takes the following CES form:

$$Q_j = \left[\int_{\omega \in \Omega_s} q_j(\omega)^{\eta} d\omega\right]^{\frac{1}{\eta}}, \; 0 < \eta < 1, \tag{A-1}$$

where $1/(1-\eta) > 1$ is the elasticity of substitution between varieties within a sector. We assume $\eta > \nu > 1$.

Denote the price of variety ω in sector j by $p_j(\omega)$. The price index of sector j is then $P_j = \left[\int_{\omega \in \Omega_s} p_j(\omega)^{-\frac{\eta}{1-\eta}} d\omega\right]^{-\frac{1-\eta}{\eta}}$. The consumer price index of the economy is thus $P = \left[\int_0^1 P_j^{1-\kappa} dj\right]^{\frac{1}{1-\kappa}}$. By choosing the aggregate consumption bundle as the numeraire, we set $P = 1$.

The model features heterogeneous firm productivity, monopolistic competitive goods markets, and CES preferences, as in Melitz (2003). Each firm faces its own downward-sloping demand. Before entry, a firm draws productivity φ from a cumulative distribution function $G(\varphi)$ over $[0, \infty)$, and the perceived *relative* productivity of female workers ($\gamma \equiv \gamma_f / \gamma_m$) from separate normal distributions as described in Section 3. Both φ and γ are assumed to be independently distributed from each other. A firm with the parameter bundle (φ, γ) selling goods in a particular sector has revenue equal to $R(\varphi, \gamma) = A^{1-\eta} y(\varphi, \gamma)^{\eta}$, where A determines the level of demand in the sector, which is taken as given by each firm. $y(\varphi, \gamma)$ is the firm's output level, which depends on both productivity and the perceived productivities of female and male workers.

A.1.2 Production

On the production side, we follow Acemoglu and Autor (2011) (AA hereafter). Consider two input types - skills and brawn inputs. Each firm hires a continuum of these tasks from female and male workers. Output of sector j combines both types of tasks based on the following CES production function:

$$Y_j = \left[\beta_j^{\frac{1}{\kappa}} S_j^{\frac{\kappa-1}{\kappa}} + \left(1-\beta_j\right)^{\frac{1}{\kappa}} B_j^{\frac{\kappa-1}{\kappa}} \right]^{\frac{\kappa}{\kappa-1}},$$

where

$$S_j = \int_{\zeta \in \Omega_{jH}} s_\zeta d\zeta \quad B_j = \int_{\zeta \in \Omega_{jB}} b_\zeta d\zeta,$$

and $\kappa_j \in [0, \infty)$ is the elasticity of substitution between skill and brawn tasks. β_j represents the importance of skill inputs relative to brawn inputs in the production of sector-j goods. A high-β sector uses S more intensively in production.

A.2 Labor Supply

Let us now turn to the labor supply side of the model. The economy is endowed with two types of workers: male and female workers. Let us denote the mass of male workers and female workers by M and F, respectively. Each worker is endowed with some skills and brawn inputs.

Consistent with the literature and empirical evidence, we assume that relative to female workers, male workers are endowed with more brawn than skills (e.g. Pitt, et al. 2012).[37] In other words, female workers have a comparative advantage in skill-intensive tasks. More formally, let θ_l^s and θ_l^b be the skill and brawn endowment of gender-l worker, respectively. These assumptions about males' (m) and females' comparative advantage imply that

$$\frac{\theta_m^S}{\theta_m^B} > \frac{\theta_f^S}{\theta_f^B}. \tag{A-2}$$

There is no other intrinsic heterogeneity in labor productivity between male and female workers, or within each gender group.

As in AA, each worker has 1 unit of time and has to decide how to allocate the time used on supplying brawn or skills. Their time budget constraints are as follows

$$t_m^B + t_m^S \leq 1;$$

$$t_f^B + t_f^S \leq 1.$$

Both female and male workers choose how much skill and brawn to supply, respectively. In this sense, the supplies of skills and brawn in the aggregate economy are endogenous. As such, each

[37] If this prediction is too strong, we can assume different distributions of brain and brawn endowments for male and female workers, with the mean brawn-to-brain ratio for the former higher than that of the latter, and the same variance.

male and female worker will make the following wages:

$$\begin{aligned} w_m &= w_B\theta_m^B t_m^B + w_S\theta_m^S\left(1-t_m^B\right); \\ w_f &= w_B\theta_f^B t_f^B + w_S\theta_f^S\left(1-t_f^B\right), \end{aligned}$$

where w_B and w_S are the wage rates for 1 unit of brawn and skills, respectively.

Because of law of one price in a frictionless labor market, the wage rate for one unit of skill supply and for one unit of brawn supply is the same regardless of which task or sector it is employed. All males workers will choose to supply brawn if

$$w_B\theta_m^B > w_S\theta_m^S \Rightarrow \frac{w_B}{w_S} > \frac{\theta_m^S}{\theta_m^B},$$

while all female workers will choose skills if

$$w_S\theta_f^S > w_B\theta_f^B \Rightarrow \frac{w_B}{w_S} < \frac{\theta_f^S}{\theta_f^B}.$$

Given assumption (A-2), it can be shown that in equilibrium, the following inequality will hold:

$$\frac{\theta_f^S}{\theta_f^B} > \frac{w_B}{w_S} > \frac{\theta_m^S}{\theta_m^B}.$$

Therefore, we have the following lemma that is crucial for the rest of the theoretical analysis.

Lemma 1 *In equilibrium with no wage arbitrage, all females choose to supply skills (S), while all males choose to supply brawn services (B).*

Proof. For the first inequality, suppose it does not hold and $\frac{\theta_f^S}{\theta_f^B} \leq \frac{w_B}{w_S}$ instead. $w_S\theta_f^S \leq w_B\theta_f^B$, which implies that all female workers will choose to supply brawn. Given assumption (A-2), $\frac{\theta_m^S}{\theta_m^B} \leq \frac{w_B}{w_S}$ and $w_S\theta_m^S \leq w_B\theta_m^B$ and all males will choose to supply brawn as well. There is no supply of skills in the economy but from above, we know that for any positive w_B and w_S, Proposition 1 shows that there will always be demand for skills. Thus, $\frac{\theta_f^S}{\theta_f^B} > \frac{w_B}{w_S}$. For the second inequality, suppose it does not hold and $\frac{\theta_m^S}{\theta_m^B} \geq \frac{w_B}{w_S} \Rightarrow w_S\theta_m^S \geq w_B\theta_m^B$, all male workers will choose to supply skills only and since we already showed that $\frac{\theta_f^S}{\theta_f^B} > \frac{w_B}{w_S} \Rightarrow w_S\theta_f^S > w_B\theta_f^B$, female workers also only supply skills. There will be no supply of brawn services in the economy, which is obviously inconsistent to what we have proved in Proposition 1. Thus, $\frac{w_B}{w_S} > \frac{\theta_m^S}{\theta_m^B}$. ■

Based on this lemma, we therefore obtain a one-to-one mapping between skill and female labor supply and brawn services and male labor supply. Specifically, total skill supply in the economy

equals $S = \theta_f^S F$ and the total brawn supply is $B = \theta_f^S M$.

A.3 Proofs

Deriving a firm's cost function in terms of γ To derive the cost function for firm with (γ, φ), we solve for the following cost minimization problem:

$$\min_{f,m} w_f f + w_m m$$

subject to

$$y = \left[\beta^{\frac{1}{\kappa}} (\gamma^{\frac{1}{\kappa-1}} f)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}. \tag{A-3}$$

First order conditions yield

$$\frac{w_f}{w_m} = \gamma^{\kappa} \left(\frac{\beta}{1-\beta}\right)^{\frac{1}{\kappa}} \left(\frac{m}{f}\right)^{\frac{1}{\kappa}} \tag{A-4}$$

Plugging this equation into (A-3) and solving for m yields

$$m(\varphi, \gamma, y) = \frac{(1-\beta) w_m^{-\kappa}}{\varphi} \left[\gamma\beta \left(\frac{1}{w_f}\right)^{\kappa-1} + (1-\beta)\right]^{\frac{\kappa}{1-\kappa}} y; \tag{A-5}$$

Plugging $m(\varphi, \gamma, y)$ into

$$f(\varphi, \gamma, y) = \frac{\beta w_f^{-\kappa}}{\varphi} \left[\gamma\beta \left(\frac{1}{w_f}\right)^{\kappa-1} + (1-\beta)\right]^{\frac{\kappa}{1-\kappa}} y; \tag{A-6}$$

Plugging these solutions and after some algebra yield the cost function as

$$\begin{aligned} c(\varphi, \gamma) &= w_f f + w_m m \\ &= \frac{1}{\varphi} \left(\beta\gamma w_f^{1-\kappa} + (1-\beta)(w_m)^{1-\kappa}\right)^{\frac{1}{1-\kappa}} y \end{aligned} \tag{A-7}$$

Proof of Proposition 2 To prove the first part of *Proposition 2* regarding the non-monotonic relationship between a firm's profits and perceived female labor productivity (γ), let us define

$$\Phi^{\pi} \equiv \frac{\pi(\varphi, \gamma)}{\pi(\varphi, 1)}$$

$$\Phi^{\pi} = \left[\frac{\gamma\beta w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}{\beta w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}\right]^{\frac{1}{\kappa-1}\frac{\eta}{1-\eta}} \left[\frac{\left(\frac{\gamma^{1-\frac{1}{\kappa}}\beta w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}{\beta\gamma w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}\right)^{\frac{\eta\kappa}{\kappa-1}} - \eta}{1-\eta}\right]$$

Let us simplify this expression by defining three constant terms that are independent of γ as:

$$\begin{aligned} a_1 &\equiv \beta w_f^{1-\kappa} > 0; \\ a_2 &\equiv (1-\beta) w_m^{1-\kappa} > 0; \\ a_3 &\equiv (\beta w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa})^{\frac{1}{\kappa-1}\frac{\eta}{1-\eta}} (1-\eta) > 0. \end{aligned}$$

We can express Φ^π as

$$\Phi^\pi = \frac{1}{a_3}\left[(a_1\gamma + a_2)^{\frac{\eta-\eta(1-\eta)\kappa}{(\kappa-1)(1-\eta)}}\left(a_1\gamma^{\frac{\kappa-1}{\kappa}} + a_2\right)^{\frac{\eta\kappa}{\kappa-1}} - \eta(a_1\gamma + a_2)^{\frac{\eta}{(\kappa-1)(1-\eta)}}\right]$$

$$\begin{aligned} \frac{\partial \Phi^\pi}{\partial \gamma} &\propto a_1 \frac{\eta - \eta(1-\eta)\kappa}{(\kappa-1)(1-\eta)}(a_1\gamma + a_2)^{\frac{\eta-\eta(1-\eta)\kappa}{(\kappa-1)(1-\eta)}-1}\left(a_1\gamma^{\frac{\kappa-1}{\kappa}} + a_2\right)^{\frac{\eta\kappa}{\kappa-1}} \\ &\quad + a_1\eta\gamma^{-\frac{1}{\kappa}}(a_1\gamma + a_2)^{\frac{\eta-\eta(1-\eta)\kappa}{(\kappa-1)(1-\eta)}}\left(a_1\gamma^{\frac{\kappa-1}{\kappa}} + a_2\right)^{\frac{\eta\kappa}{\kappa-1}-1} \\ &\quad - \frac{a_1\eta^2}{(\kappa-1)(1-\eta)}(a_1\gamma + a_2)^{\frac{\eta}{(\kappa-1)(1-\eta)}-1} \\ &\propto b_1(\gamma) - b_2(\gamma), \end{aligned}$$

where $b_1(\gamma) = \left(\frac{1-(1-\eta)\kappa}{(\kappa-1)(1-\eta)} + \frac{a\gamma^{\frac{\kappa-1}{\kappa}} + b\gamma^{-\frac{1}{\kappa}}}{a\gamma^{\frac{\kappa-1}{\kappa}} + b}\right)\left(a\gamma^{\frac{\kappa-1}{\kappa}} + b\right)^{\frac{\eta\kappa}{\kappa-1}}$ and $b_2(\gamma) = \frac{\eta}{(\kappa-1)(1-\eta)}(a\gamma + b)^{\frac{\eta\kappa}{\kappa-1}}$.

It can be shown that $b_1(\gamma) > b_2(\gamma)$ for $\gamma < 1$; $b_1(\gamma) < b_2(\gamma)$ for $\gamma > 1$, and $b_1(\gamma) = b_2(\gamma)$ for $\gamma = 1$. These inequalities hold regardless of the value of $\kappa > 1$. In sum, Φ^π and $\pi(\varphi, \gamma)$ attains its maximum when $\gamma = 1$.

To prove the second part of *Proposition 2* regarding a negative relationship between revenue TFP and γ. Let us define revenue TFP as

$$TFPR = \frac{R(\varphi, \gamma)}{\left[\beta^{\frac{1}{\kappa}} f(\varphi, \gamma)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m(\varphi, \gamma)^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}}$$

$$TFPR = \frac{R(\varphi, \gamma)}{\left[\beta^{\frac{1}{\kappa}} f(\varphi, \gamma)^{\frac{\kappa-1}{\kappa}} + (1-\beta)^{\frac{1}{\kappa}} m(\varphi, \gamma)^{\frac{\kappa-1}{\kappa}}\right]^{\frac{\kappa}{\kappa-1}}}$$

After some tedious algebra we obtain

$$TFPR = \eta^{-1} c(\gamma) B(\gamma)^{-\frac{(1-\eta)\kappa}{\kappa-1}}$$

where $c(\gamma) = \left[\gamma\beta w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}\right]^{\frac{1}{1-\kappa}}$ and $B(\gamma) = \frac{\beta\gamma^{\frac{\kappa-1}{\kappa}} w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}{\beta\gamma w_f^{1-\kappa} + (1-\beta) w_m^{1-\kappa}}$, as described in the main text. Since $c'(\gamma) < 0$, if we can show that $B'(\gamma) > 0$, then we know that $\frac{\partial TFPR}{\partial \gamma} < 0$.

$$
\begin{aligned}
\frac{dB(\gamma)}{d\gamma} &\propto \left(1-\frac{1}{\kappa}\right)\gamma^{-\frac{1}{\kappa}}\beta w_f^{1-\kappa}\left[\beta\gamma w_f^{1-\kappa}+(1-\beta)\,w_m^{1-\kappa}\right]-\beta w_f^{1-\kappa}\left[\gamma^{1-\frac{1}{\kappa}}\beta w_f^{1-\kappa}+(1-\beta)w_m^{1-\kappa}\right] \\
&= (1-\beta)\,w_m^{1-\kappa}\left[\gamma^{-\frac{1}{\kappa}}\left(1-\frac{1}{\kappa}\right)-1\right]-\frac{1}{\kappa}\beta\gamma^{1-\frac{1}{\kappa}}w_f^{1-\kappa}.
\end{aligned}
$$

It can be easily shown that

$$
\frac{d^2B(\gamma)}{d\gamma^2}=(1-\beta)\,w_m^{1-\kappa}\left[\left(\frac{1}{\kappa^2}-\frac{1}{\kappa}\right)\gamma^{-\frac{1}{\kappa}-1}-1\right]-\frac{1}{\kappa}\beta\left(1-\frac{1}{\kappa}\right)\gamma^{-\frac{1}{\kappa}}w_f^{1-\kappa}<0.
$$

Moreover, when $\gamma=0$, $\frac{dB(\gamma)}{d\gamma}\to\infty$. When $\gamma=\infty$, $\frac{dB(\gamma)}{d\gamma}\to-\infty$. Therefore, we can confirm that $\frac{dB(\gamma)}{d\gamma}<0$ for $\gamma\in(0,\infty)$.

We can extend the expression for $TFPR$ into

$$
\begin{aligned}
\ln TFPR\,(\varphi,\gamma) &\propto \ln c(\gamma)-\frac{(1-\eta)\,\kappa}{\kappa-1}\ln B(\gamma) \\
&\propto (1-(1-\eta)\,\kappa)\ln c(\gamma)-\frac{(1-\eta)\,\kappa}{\kappa-1}\ln\left[\gamma^{-\frac{1}{\kappa}}\beta\gamma w_f^{1-\kappa}+(1-\beta)w_m^{1-\kappa}\right] \\
&\propto \frac{(1-\eta)\,\kappa-1}{\kappa-1}\ln\left[\gamma+\frac{1-\beta}{\beta}\left(\frac{w_m}{w_f}\right)^{-\kappa}\frac{w_m}{w_f}\right] \\
&\quad -\frac{(1-\eta)\,\kappa}{\kappa-1}\ln\left[\gamma^{1-\frac{1}{\kappa}}+\frac{1-\beta}{\beta}\left(\frac{w_m}{w_f}\right)^{-\kappa}\frac{w_m}{w_f}\right].
\end{aligned}
$$

Let us derive of marginal revenue products. For female workers:

$$
\begin{aligned}
MRP_f &\equiv \frac{\partial R}{\partial f} \\
&= c(\gamma)^{1-\kappa(1-\eta)}\left[\beta\gamma^{\frac{\kappa-1}{\kappa}}w_f^{1-\kappa}+(1-\beta)w_m^{1-\kappa}\right]^{\frac{\kappa\eta}{\kappa-1}-1}\gamma^{\frac{-1}{\kappa}}w_f \\
&= \left[\frac{\beta\gamma w_f^{1-\kappa}+(1-\beta)w_m^{1-\kappa}}{\beta\gamma^{\frac{\kappa-1}{\kappa}}w_f^{1-\kappa}+(1-\beta)w_m^{1-\kappa}}\right]^{\frac{1-\kappa(1-\eta)}{1-\kappa}}\gamma^{\frac{-1}{\kappa}}w_f \\
&= B(\gamma)^{-\frac{\kappa(1-\eta)-1}{\kappa-1}}\gamma^{\frac{-1}{\kappa}}w_f
\end{aligned}
$$

Similarly MRP for male workers can be derived as

$$
MRP_m=B(\gamma)^{-\frac{\kappa(1-\eta)-1}{\kappa-1}}w_m.
$$

Figure 1: Density of Female Share in Firm Employment (2004)

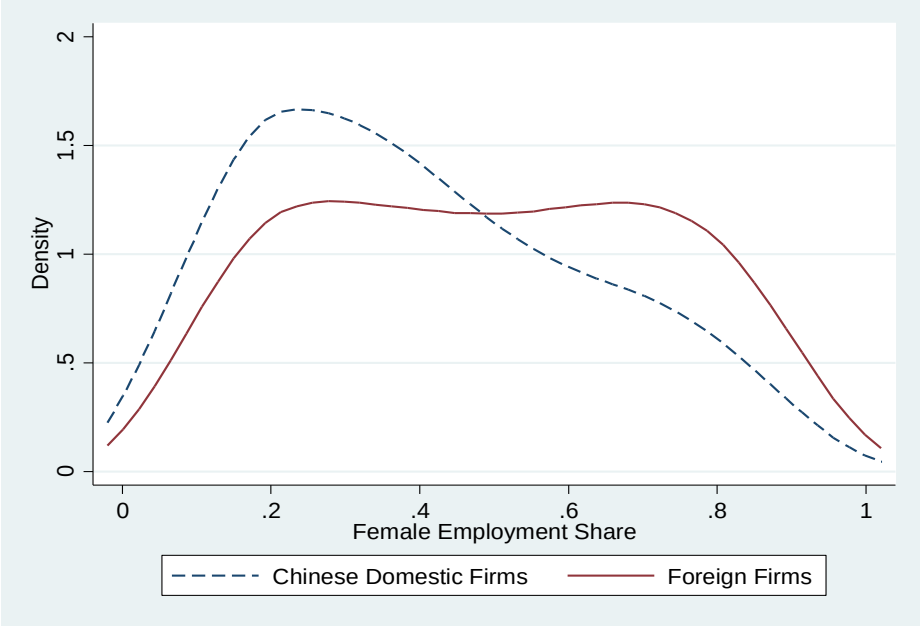


Figure 2: Density of Female Share in Firm Employment (2004)
(controlling for 4-digit industry Fixed Effects)

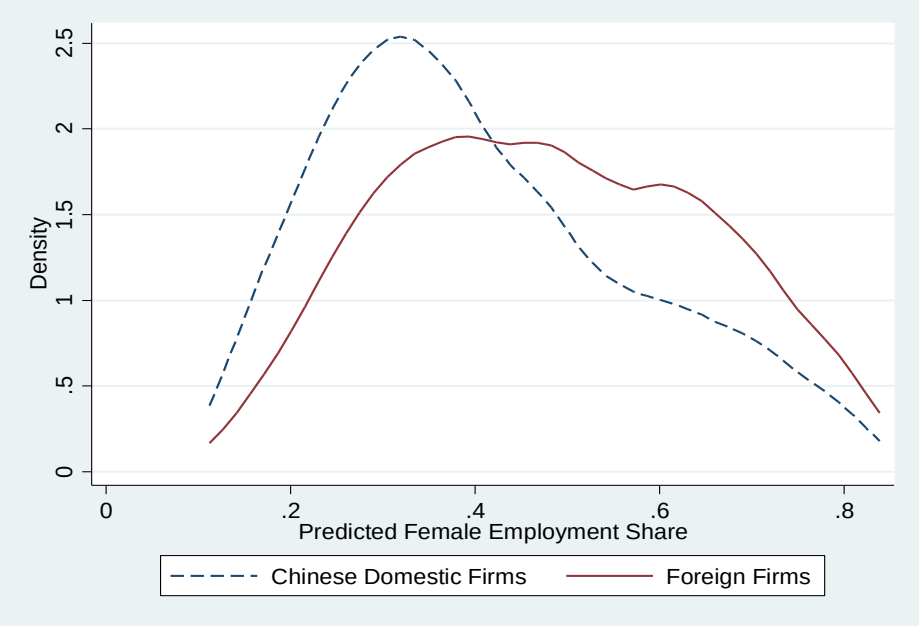


Figure 3: (Average) Female Shares in Domestic and Foreign Firms' Employment by Sector (2004)

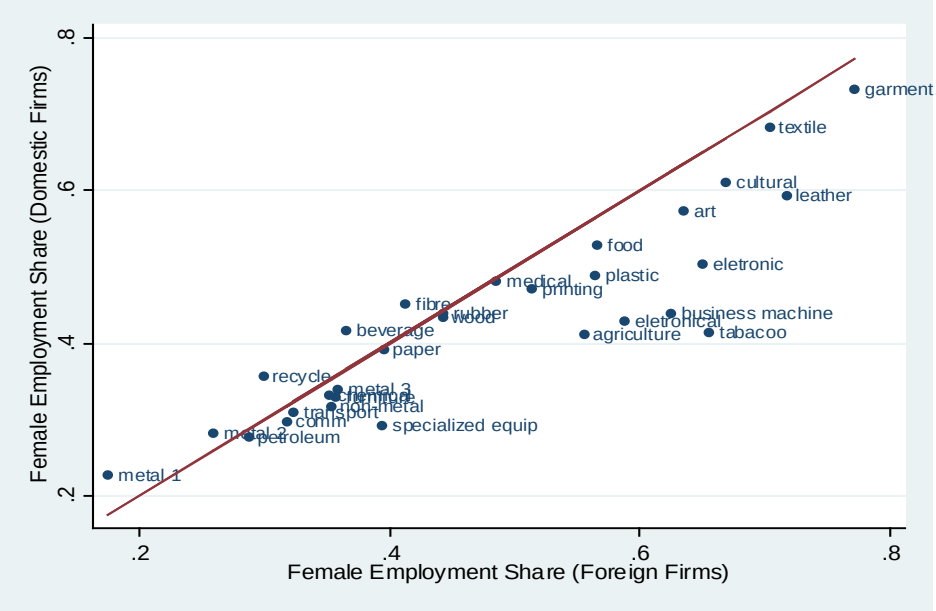
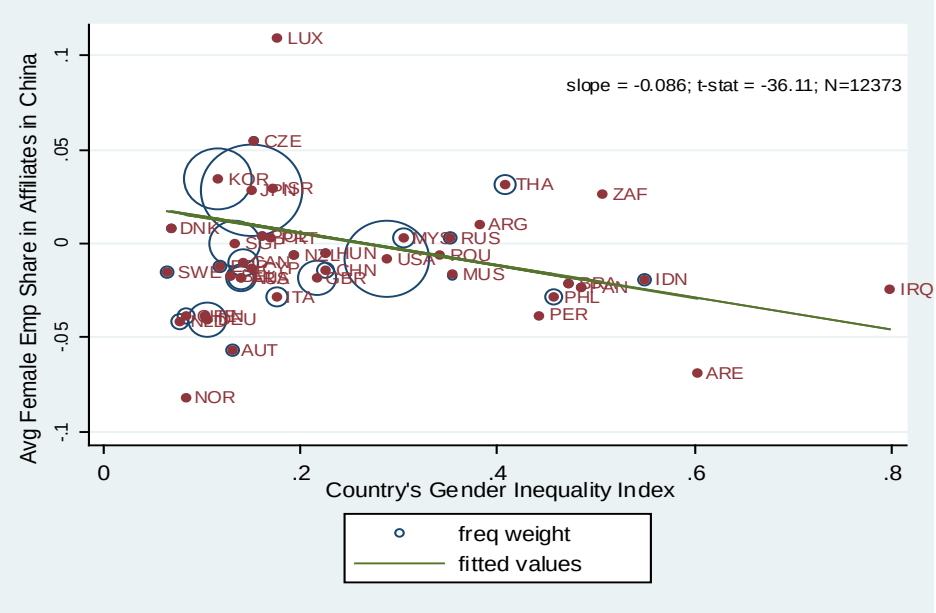


Figure 4: (Average) Female Share in Foreign Firms' Employment by Country of Origin



Notes: Average Female Emp (vertical axis) is demeaned from industry and province means. The linear plot is obtained based on weighted-OLS, with log(GDP) of the country of origin controlled for.

Figure 5: Variance of (log) discrimination factor and (lagged) Foreign Firms' Output Share by 2-digit Industry

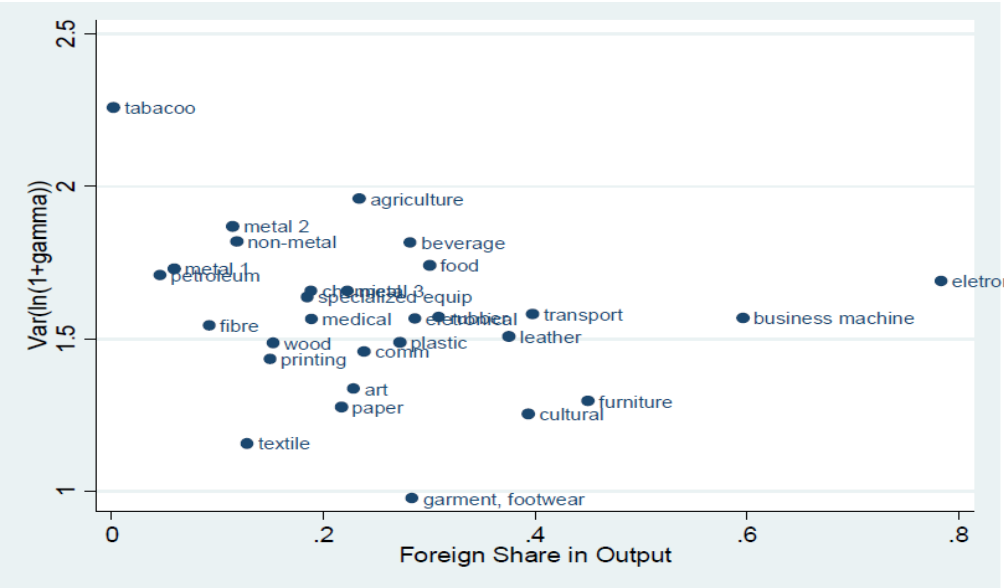


Table 1: Countries's UNDP Gender Inequality and World Value Survey Indices
(Top and Bottom 5 Countries)

	Country	Index		Country	Index
Panel A: UNDP Gender Inequality Index (High value means more unequal)					
1	Sweden	0.065	1	Saudi Arabia	0.685
2	Denmark	0.068	2	India	0.637
3	Netherlands	0.077	3	UAE	0.602
4	Norway	0.083	4	Indonesia	0.549
5	Switzerland	0.084	5	Cambodia	0.548
Panel B: World Value Survey Score (High value means more equal)					
1	Sweden	0.876	1	India	0.446
2	Norway	0.875	2	Iran	0.497
3	France	0.815	3	Malaysia	0.556
4	Finland	0.797	4	Indonesia	0.569
5	Canada	0.792	5	Vietnam	0.571

Note: Higher gender inequality index or lower World Value Survey score indicates greater gender inequality.
Source: United Nations Development Program and World Value Survey.

Table 2: Summary Statistics of the 2004 Data

Variable	N	Mean	St Dev.
Country Level			
Gender inequality index	137	0.419	0.195
World Value Survey score	58	0.649	0.124
ln(GDP per capita)	137	8.060	1.671
Industry Level (Four Digit Industry Code)			
Female comparative advantage	482	0.268	0.105
FDI presence (4-digit industry)	482	0.344	0.218
Herfindhal index	482	0.049	0.076
City Level (Four Digit Geographic Code)			
FDI presence (city)	345	0.155	0.182
Firm Level			
Female employment share			
all workers	258,899	0.411	0.243
unskilled workers	240,787	0.437	0.299
skilled workers	255,239	0.370	0.230
domestic Chinese firms	202,536	0.390	0.236
foreign invested enterprises (FIEs)	28,450	0.482	0.256
Likelihood of a female manager			
all firms	217,181	0.246	0.277
domestic Chinese firms	170,501	0.243	0.277
foreign invested enterprises (FIEs)	23,243	0.255	0.273
Other firm characteristics used as independent variables			
computer intensity	278,507	0.147	19.336
R&D intensity	272,948	0.031	0.054
ln(TFP)	241,866	-0.972	1.071
skill intensity	278,507	0.012	0.053
capital intensity	255,449	100.879	1,046
output	275,460	72,743	656,030
profit rate	249,424	0.025	0.084
age	278,563	8.934	10.891

Source: NBS above-scale annual survey of industrial firms (2004).

Note: See definitions in Table A1 in the appendix.

Table 3: Gender Cultural Transfer Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Female share in total employment			Female share in unskilled emp	Female share in skilled emp	Prob. of female manager	Female share in total employment
Gender Inequality index (GII)	-0.059	-0.099		-0.113	-0.073	-0.123	0.049
	(-2.57)**	(-6.17)***		(-4.89)***	(-4.04)***	(-1.78)*	(0.87)
World Value Survey score			0.072				
			(2.09)**				
GII * Female CA							-0.456
							(-2.51)**
ln(gdppc)		0.003	0.005	0.006	0.001	0.005	0.001
		(0.95)	(1.22)	(1.57)	(0.37)	(0.82)	(0.28)
Computer intensity		-0.0007	-0.0009	-0.049	-0.00057	-0.032	-0.0005
		(-1.84)*	(-1.73)*	(-4.27)***	(-1.27)	(-4.46)***	(-3.07)***
R&D intensity		-0.018	-0.008	0.013	-0.017	-0.009	-0.040
		(-1.81)*	(-1.30)	(0.86)	(-1.47)	(-4.98)***	(-2.18)**
ln(TFP)		-0.028	-0.023	-0.021	-0.027	-0.026	-0.024
		(-13.25)***	(-18.53)***	(-6.40)***	(-8.02)***	(-12.47)***	(-7.71)***
Skill intensity		0.029	-0.298	-2.156	0.248	-0.032	0.027
		(0.29)	(-5.54)***	(-7.24)***	(2.31)**	(-0.65)	(0.38)
ln(capital intensity)		-0.040	-0.031	-0.036	-0.026	-0.087	-0.038
		(-24.83)***	(-28.34)***	(-15.40)***	(-14.70)***	(-9.84)***	(-12.29)***
ln(output)		0.020	0.016	0.012	0.014	0.014	0.018
		(11.72)***	(16.33)***	(4.37)***	(7.54)***	(7.69)***	(6.93)***
ln(wage rate)		-0.023	-0.031	-0.026	-0.014	-0.084	-0.023
		(-8.25)***	(-12.34)***	(-6.30)***	(-4.48)***	(-8.32)***	(-6.82)***
ln(firm age)		0.004	0.006	0.003	0.003	0.004	0.005
		(2.36)**	(8.76)***	(1.03)	(1.56)	(1.88)*	(2.24)**
Industry (4-digit) FE	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y
Nb Obs	12,345	11,504	9,365	10,416	11,465	7,884	10,693
Adj. R-sq	0.515	0.568	0.546	0.463	0.363	0.156	0.576

Notes: t-statistics based on standard errors clustered at the four-digit industry (482 categories) are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Gender Cultural Spillover (Across Industries)

	(1)	(2)	(3)	(4)	(5)
Firm Sample:	2004	2004	2004-2007 Panel		
Dependent Variable:	Female share in total employment	Probability of female manager	Female share in total employment		
FDI in industry	0.321	0.047	0.032	0.045	-0.012
	(4.11)***	(3.43)***	(5.21)***	(4.21)***	(-1.42)
FDI in industry* average GII				-0.049	
				(-3.33)***	
FDI in industry* average WVS					0.067
					(3.71)***
Import share	-0.132	-0.213	-0.017	-0.016	-0.018
	(-3.62)***	(-1.93)*	(-1.53)	(-2.53)**	(-2.09)**
Herfindhal index	-0.122	0.025	-0.035	-0.055	-0.051
	(-3.69)***	(0.56)	(-2.34)**	(-3.69)***	(-3.71)***
Controls	Y	Y	Y	Y	Y
Province fixed effects	Y	Y			
Year fixed effects			Y	Y	Y
Firm fixed effects			Y	Y	Y
Nb Obs	187,885	155,717	800,907	800,907	800,907
Adj. R-sq	0.138	0.046	0.754	0.794	0.793

Notes: All regressions include R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. The 2004 regressions include additional control of skill intensity. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Gender Cultural Spillover (Across Cities)

	(1)	(2)	(3)	(4)	(5)
Firm Sample:	2004	2004	2004-2007 Panel		
Dependent Variable:	Female share in total employment	Probability of female manager	Female share in total employment		
FDI in city	0.095	0.048	0.092	0.108	0.046
	(4.57)***	(4.52)***	(5.17)***	(5.36)***	(3.34)***
FDI in city* average GII				-0.152	
				(1.89)*	
FDI in city* average WVS					0.092
					(2.03)**
Import share	-0.121	-0.015	-0.017	-0.019	-0.018
	(-2.72)***	(-2.04)**	(-2.46)***	(-3.07)***	(2.23)***
Herfindhal index	-0.434	-0.124	-0.027	-0.038	-0.025
	(-1.51)	(-2.89)***	(-0.85)	(-1.70)*	(-1.51)
Controls	Y	Y	Y	Y	Y
Year fixed effects			Y	Y	Y
Firm fixed effects			Y	Y	Y
Nb Obs	187,885	149,594	765,457	765,457	765,457
Adj. R-sq	0.068	0.015	0.797	0.810	0.803

Notes: All regressions include R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. The 2004 regressions include additional control of skill intensity. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Female Employment Shares and Profits

	(1)	(2)	(3)	(4)	(5)	(6)
Firm Panel Sample:	All	Domestic	Foreign	All	Domestic	Foreign
Dependent Variable:			Profit/ Sales			
Female share	0.002	0.002	-0.000	0.003	0.002	0.006
	(2.02)***	(2.14)***	(-0.05)	(3.13)***	(1.75)*	(3.27)***
R&D intensity				-0.000	-0.000	-0.000
				(-0.86)	(-0.65)	(-0.75)
ln(capital intensity)				0.002	0.003	-0.001
				(8.44)***	(10.62)***	(-0.96)
ln(wage rate)				0.005	0.005	0.006
				(13.88)***	(11.06)***	(10.30)***
ln(firm age)				0.001	0.001	0.005
				(9.05)***	(4.81)***	(8.83)***
ln(employment)				0.010	0.009	0.015
				(23.89)***	(18.31)***	(16.31)***
Fixed Effects			Year and Firm			
Nb Obs	1,067,128	837,234	229,894	1,060,883	832,271	228,612
Adj. R-sq	0.531	0.544	0.515	0.535	0.549	0.521

Notes: t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Gender Cultural Spillover (Heterogeneous Effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	2004-2007 Chinese Domestic Firms							
Dependent Variable:	Female share in total employment							
FDI in industry	-0.018	0.054	0.041	0.044	0.028	0.046	0.036	0.049
	(-2.14)**	(2.23)**	(3.56)***	(4.25)**	(2.61)***	(2.15)**	(2.15)***	(2.69)***
FDI * GII		-0.342		-0.035		-0.057		-0.073
		(-1.90)*		(-2.32)**		(-1.87)*		(-2.89)***
FDI * female CA	0.181							
	(4.23)***							
FDI * GII * female CA		0.843						
		(2.29)**						
FDI * Herfindhal			-0.176					
			(-3.03)***					
FDI * GII* Herfindhal				-0.578				
				(-2.21)**				
FDI * ln(TFP)					-0.013			
					(-2.89)***			
FDI * GII* ln(TFP)						-0.025		
						(-0.45)		
FDI * Std Dev GII							-0.031	
							(-0.35)	
FDI * GII * Std Dev GII								0.151
								(0.64)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Fixed Effects	Firm and Year							
Nb Obs	800,907	800,907	800,907	800,907	800,907	800,907	792,922	792,922
Adj. R-sq	0.793	0.794	0.793	0.794	0.794	0.794	0.794	0.794

Notes: All regressions include Herfindhal index, import share, R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Female Employment Shares and Exits

	(1)	(2)	(3)
Sample	2004-2006 domestic firms		
Dependent variable	Dummy (Firm exit from the sample in the following year)		
FDI in industry	-0.016	-0.036	-0.374
	(-0.33)	(-0.57)	(-2.81)***
Female share	-0.029	-0.027	-0.031
	(-3.24)***	(-3.08)***	(-3.29)***
FDI * female share	0.009	0.142	0.051
	(0.42)	(3.08)***	(1.44)
FDI * GII		0.121	
		(0.46)	
FDI * GII * female share		-0.740	
		(-3.17)***	
FDI * female CA			1.361
			(2.53)***
FDI * female CA * female share			-0.128
			(-1.99)**
Controls	Y	Y	Y
Year fixed effects	Y	Y	Y
Industry fixed effects	Y	Y	Y
N	563,195	559,413	563,195
adj. R-sq	0.053	0.053	0.053

Notes: All regressions include the sector's herfindhal index, sector's import share, R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Table A1: Variable Definitions and Data Sources

Variable	Definition
Female share	Number of female workers divided by total employment.
Female share unskilled	Number of female unskilled workers divided by total number of unskilled workers. Unskilled labor is defined as workers with junior high school education level or below.
Female share skilled	Number of female skilled workers divided by total number of skilled workers. Skilled labor is defined as workers with at leat senior high school education level.
Gender Inequality Index (GII)	Country-level measure of gender inequality. Source: UNDP.
WVS score	World Value Survey Score in 2005. It is calculated based on Questions V44, V61 and V63 in the survey. Source: World Value Survey.
Female probability of legal person representative	The probability of a Chinese character being the last character of a woman's name. It is calculated using equation (2) in the text.
ln(gdppc)	Natural log of the GDP per capita in 2004. Source: World Bank.
Computer intensity	Number of computers/total employment.
R&D/value added	R&D expenditure/total value added.
ln(TFP)	Total factor productivity calculated with Olley-Pakes procedure.
ln(capital intensity)	Natural log of real capital stock/total employment. Real capital stock is calculated using the prepetual inventory method in Brandt et al. (2012).
ln(output)	Natural log of total output.
ln(wage rate)	Natural log of total wage/total employment.
ln(age)	Natural log of the number of years since the starting date of the firm.
Profit rate	Total profit/sales revenue
FDI presence in industry	Share of foreign invested firms in total output of a 4-digit industry.
FDI presence in city	Share of foreign invested firms in total output of a city.
Female comparative advantage	World average share of women in total employment by industry. Source: Do, Levchenko and Raddatz (2014).

Table A2: Ranking of Chinese Characters as the Last Character in Female and Male Names

	Characters with the highest female name probability		Characters with the lowest female name probability	
Rank	Character	female prob.	Character	female prob.
1	娟	0.997	彪	0.008
2	媛	0.996	法	0.012
3	娥	0.996	刚	0.012
4	娇	0.995	财	0.018
5	婵	0.994	山	0.019
6	姐	0.992	豪	0.022
7	菊	0.992	泰	0.023
8	花	0.990	强	0.024
9	翠	0.989	武	0.025
10	莉	0.988	魁	0.026

Source: Authors' calculation using 20% extract of the 2005 1% Population Census.

Table A3: Number of Foreign Firms (Top 20 Source Countries)

	2004	2004-2007
Country	Number of Firms	
JPN	3840	14736
USA	2361	8732
KOR	1705	6612
SGP	892	3345
DEU	491	1855
AUS	486	1779
GBR	391	1484
CAN	278	1012
MYS	161	603
ITA	158	602

Source: NBS above-scale annual survey of industrial firms (2004 cross-section and 2004-2007 panel).

Table A4: The Impact of FDI on Gender Wage Inequality at the City-Level

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	ln(female wage/male wage) Estimated Using All Individuals			ln(female wage/male wage) Estimated Using Individuals in Manufacturing Sector Only		
FDI in city	0.192	0.189	0.407	0.314	0.322	0.633
	(2.26)**	(2.09)**	(1.93)*	(2.05)**	(1.92)*	(1.69)*
FDI in city * average GII			-0.665			-0.532
			(-0.91)			(-0.72)
Average years of schooling		0.015	0.019		-0.004	-0.001
		(0.76)	(0.83)		(-0.16)	(-0.35)
ln(average wage rate)		-0.035	-0.041		0.038	0.034
		(-0.72)	(-0.68)		(0.73)	(0.78)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	723	723	618	711	711	592
adj. R-sq	0.484	0.483	0.458	0.367	0.365	0.328

Notes: We conduct this exercise in two stages. In the first stage, we run individual level Mincer-type wage regressions for each city using the urban household data 2004-2007, and obtain the coefficient of the female dummy. We do this using all individuals and using those individuals in manufacturing sector only. In the second stage, we run city-level regressions using the estimated female dummy from the first stage as the dependent variable. This table reports the regression results of the second stage. z-statistics based on bootstrapped standard errors are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Top and Bottom 10 Sectors based on Female Comparative Advantage

	Top 10 Sectors	Female Share		Bottom 10 Sectors	Female Share
1	Textile Wearing Apparel, Footware and Caps	0.600	1	Ferrous Metals	0.110
2	Textile	0.487	2	Petroleum, Coking, Processing of Nuclear Fuel	0.123
3	Leather, Fur, Feather and Related Products	0.420	3	Non-ferrous Metals	0.125
4	Communication Equipment, Computers and Other Electronic Equipment	0.405	4	Transport Equipment	0.136
5	Instruments and Machinery for Cultural Activity and Office Work	0.403	5	General Purpose Machinery	0.150
6	Artwork and Other Manufacturing	0.380	6	Metal Products	0.155
7	Articles For Culture, Education and Sport Activities	0.380	7	Timber, Wood, Bamboo, Rattan, Palm and Straw Products	0.160
8	Electrical Machinery and Equipment	0.338	8	Non-metallic Mineral Products	0.175
9	Tabacco	0.330	9	Furniture	0.190
10	Printing, Reproduction of Recording Media	0.323	10	Recycling and Disposal of Waste	0.210

Note: World average female share in total employment by sector. Source: Do, Levchenko, and Raddatz (2014).

Table A6: Gender Cultural Spillover (All Independent Variables Lagged by One Year)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:				2004-2007			
Dependent Variable:				Female share in total employment			
lag FDI in industry	0.027	0.060	-0.021	-0.023	0.071	0.032	0.062
	(3.56)***	(4.76)***	(-1.44)	(-1.23)	(2.45)**	(5.03)***	(5.83)**
lag FDI in industry* lag average GII		-0.093			-0.419		-0.212
		(-5.01)***			(-3.28)**		(-4.83)***
lag FDI in industry* lag average WVS			0.057				
			(2.98)***				
lag FDI in industry* lag female comparative advantage				0.189			
				(6.64)***			
lag FDI in industry* lag average GII* lag female comparative					0.774		
					(2.86)***		
lag FDI in industry * lag Herfindhal index						-0.067	
						(-1.45)	
lag FDI in industry * lag average GII* lag Herfindhal index							0.201
							(0.69)
lag Herfindhal index	-0.045	-0.046	-0.051	-0.066	-0.031	-0.022	-0.025
	(-2.01)*	(-2.62)***	(-2.69)***	(-2.18)**	(-1.93)*	(-1.78)*	(-1.82)*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	684,561	684,561	684,561	684,561	684,561	684,561	684,561
adj. R-sq	0.809	0.796	0.795	0.809	0.809	0.794	0.809

Notes: All regressions include import share, lags of R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Gender Cultural Spillover (Employment Weighted measure for FDI)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:				2004-2007			
Dependent Variable:				Female share in total employment			
FDI in industry	0.033	0.041	0.015	0.038	0.043	0.036	0.048
	(3.12)***	(5.01)***	(2.05)**	(1.86)*	(1.77)*	(5.68)***	(5.19)***
FDI in industry* average GII		-0.032			-0.043		-0.023
		(-3.31)***			(-3.39)**		(-2.54)**
FDI in industry* average WVS			0.056				
			(2.96)***				
FDI in industry* female comparative advantage				-0.012			
				(-0.86)			
FDI in industry* average GII* female comparative advantage					0.028		
					(2.43)**		
FDI in industry * Herfindhal index						-0.13	
						(-1.89)*	
FDI in industry * average GII*							0.031
							(0.23)
Herfindhal index	-0.055	-0.059	-0.044	-0.033	-0.072	-0.029	-0.038
	(-1.82)*	(-3.79)***	(-3.44)***	(-2.88)***	(-1.93)*	(-1.41)	(-1.99)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	800,907	800,907	800,907	800,907	800,907	800,907	800,907
adj. R-sq	0.794	0.794	0.794	0.793	0.794	0.794	0.794

Notes: All regressions include import share, R&D intensity, ln(TFP), ln(capital intensity), ln(output), ln(wage rate) and ln(firm age) as control variables. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.