FDI and Cross-Country Diffusion of Culture: A Firm-Level Analysis of Gender Inequality in China*

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Abstract

This paper examines whether and how foreign direct investment (FDI) may lead to cultural convergence across countries. Using gender culture as an example, we study whether FDI may change foreign affiliates and domestic firms' biases towards female workers in the host country. To guide our empirical exploration, we build a parsimonious multi-sector task-based model that features heterogeneity in firms' productivity and their biases towards female workers. Discrimination lowers profits and productivity. Through competition and imitation, domestic firms increase female employment in response to increased FDI inflow. Using comprehensive manufacturing firm-level data from China over 2004-2007, we find evidence to support our model predictions. Foreign invested firms (FIEs) from countries with lower gender inequality tend to employ proportionately more female workers and are more likely to appoint female managers. In addition to gender cultural transfer within multinational firm boundary, we find evidence of gender cultural spillover from FIEs to Chinese local firms. Such effects are stronger in sectors in which females have a comparative advantage, for the less productive firms, and from FIEs whose home countries are less biased against women. These results support the predictions of our model and show that FDI lowers gender inequality through channels beyond the competition effect proposed by Becker (1957). Our study complements the existing literature on FDI spillover, which focuses primarily on technology spillover from foreign firms.

Key Words: FDI, Culture, Gender Inequality

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1 Introduction

Gender inequality is a global phenomenon. Not only that it is unjust on many grounds, it can lead to huge economic loss (Hsieh et al., 2013). Social scientists have for years argued that cultural differences are behind the varying levels of gender inequality across countries.[1] Eliminating biases against women is hard, as prejudices against certain groups in society often have their deep historical roots. Policies, such as affirmative actions, may have limited effects on these slow-moving institutions (Roland, 2004).

This paper studies how economic globalization may lead to cultural convergence across countries in terms of biases against women. Different from recent studies that emphasize how trade liberalization may induce competition and/or industrial specialization that favor women (e.g., Juhn et al., 2013), we focus on whether and how foreign direct investment (FDI) transfers culture within multinational firm boundary and eventually to local firms in the host country.

To guide our empirical exploration, we build a parsimonious multi-sector model based on the task-based approach proposed by Acemoglu and Autor (2011). In the model, production of goods requires a continuum of tasks, which can be completed using skill and physical (brawn) labor inputs. Sectors differ in their reliance on skill-intensive versus brawn-intensive tasks. The economy is endowed with an equal amount of female and male labor supply, with female workers having a comparative advantage in skills. We show that production functions micro-founded on tasks with different skill intensity can ultimately be expressed as a Cobb-Douglas function with constant exponents to female and male labor, respectively.

Our model features heterogeneity in firms' productivity and their degree of biases towards female workers. Domestic firms that discriminate women more have a lower female-to-male employment ratio than the optimal one, thus suffering from lower profits, all else being equal. Foreign direct investment raises wages for all workers and thus reduce profits for all existing firms. In addition, FDI illustrates a more profitable female employment share to domestic firms. Through both competition and imitation, local firms are induced by FDI to increase their female employment. The spillover effect is increasing in the prevalence of FDI in the same sector or city. The effects are also stronger in sectors in which females have a comparative advantage, for the less productive firms, and from foreign invested firms (FIEs) whose home countries are less biased against women. Our empirical results support the predictions of the model and show that FDI lowers gender inequality in addition to the traditional competition effect proposed by Becker (1957).

Figure 1 shows the structure of the empirical analysis. We first illustrate the cultural transfer -

[1] See, for instance, Inglehart and Norris (2003).

that multinationals carry their home countries' gender culture to their affiliates in China, which in turn affect their female employment shares. The transfer of gender culture could happen through standardized human resource policies across all foreign affiliates of a multinational firm or through different management styles by expatriates. A documentation of this specific cultural transfer within multinational firm boundary is interesting of its own right and to our understanding, has not been provided before. Then we show the cultural spillover - that FIEs in China could change the gender culture of Chinese firms through both the competition effect and the imitation effect.

We study China not only because it is one of the largest recipients of FDI, but also because its biases against women have cultural root in the Confucius philosophy, which, perhaps implicitly, promotes social and even physical oppression of women. In the traditional Chinese patriarchal society, males were viewed as superior. A woman was supposed to follow the lead of the males in her family, especially the father before marriage and the husband afterwards. Confucians believed that the strict obligatory role for women was a cornerstone for social order and social stability.

After the founding of PRC, gender inequality was significantly reduced, as a result of Mao's egalitarian philosophy. 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. Women's labor force participation rate soared. More women became leaders in the government and role model workers.

When the reform started in the late 1970s, unfortunately, gender inequality in labor market increased again. Women had to compete in a new labor market, but the playing field was not even. Market reforms often led to a return to discriminatory practices against women (Cai, Zhao and Park, 2008; Gustafsson and Li, 2000). Consequently, despite recent economic success, gender inequality is still widespread in China. 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.

The main data set for this paper is from the Annual Industrial Firm Surveys conducted by China's National Bureau of Statistics (NBS) over 2004-2007. We merge the NBS data set with Ministry of Commerce's FDI surveys to obtain the information on the country of origin of each FIE. We study gender inequality using a firm-level measure of gender inequality: female share in total employment, which we can further distinguish within skilled and less skilled employment. An alternative measure of gender inequality at the firm-level is the probability that a firm's legal person representative is a woman.[2] Our measures of gender inequality culture at the country level come from UNDP gender inequality index and World Value Survey.

We find supporting evidence for model predictions in both cultural transfer and cultural spillover. In the first part, we show that compared to Chinese firms, FIEs are more likely to hire women and are also more likely to appoint women as the legal person representatives. Our cultural transfer regression results reveal that FIEs from countries that have a lower gender inequality tend to have higher female employment share and higher probability of legal person representatives. These results hold within narrowly defined industries (over 480) and are robust to the control of province fixed effects and a wide range of firm characteristics, such as technology. We find stronger gender cultural transfer effect within wholly-owned foreign firms, compared to joint ventures. To the extent that larger equity ownership implies more control by the multinational parents' over their affiliates' decisions, the findings of stronger effects are consistent with our hypothesis that gender culture is transferred from the headquarter to the foreign affiliate.

The second part of the empirical analysis focuses on identifying the presence of gender cultural spillover. To this end, we adopt the estimation strategy from the FDI spillover literature (Aitken and Harrison, 1997; Javorcik, 2004), but instead of exploring technology or knowledge spillover, we focus on the spillover of cultural values. We explicitly control for competition and technology transfer effects and find that FDI still has an impact on Chinese local firms' female employment share and female probability of legal person representatives. Consistent with the predictions of the model, we find that firms with less gender inequality appears to be more productive. The FDI cultural spillover effect is stronger in the female comparative advantage sectors. In response to the FDI inflow, less productive firms reduce discrimination more than the productive ones. We also find that FDI impact on Chinese local firms depends on the FDI country of origin. The differential spillover effects across countries of origin implies that the FDI effect on gender employment ratio is above and beyond the traditional forces due to increased competition.

This paper contributes to several strands of literature spanning broad social science disciplines. First, it contributes to the literature on gender inequality by analyzing an unexplored channel - gender cultural diffusion through FDI. In both developed and developing countries, gender inequality can be observed in the labor market (Altonji and Blank, 1999; Autor and Wasserman, 2013), courts (Rhode, 1991; Iyer et al., 2012), and families (Almond and Edlund, 2008; Wei and Zhang, 2011a). To the extent that women account for about half of world population, a more equal treatment of women and their talent can certainly lead to huge economic and social benefits. However, both gender culture and the institutions that it constitutes are hard to change in the short run. Our

[2] As we will soon explain in the data section, legal person representative in China is either chairman or CEO of the firms. We infer the gender of legal person representatives by studying their names.

paper suggests that external forces such as FDI can help reduce the gender inequality.

Recent economics research examines the economic cost of discrimination (Mortvik and Spant, 2005; Cavalcanti and Tavares, 2007; Hsieh et al., 2013). Hsieh et al. (2013) estimate the contribution of decreasing discrimination to the U.S. productivity growth. They find that 15 to 20 percent of the growth of aggregate output per worker from 1960 to 2008 could be explained by the more efficient allocation of talent between gender and racial groups. Complementing the findings of Hsieh et al. (2013), we will provide the first piece of evidence on the cost of discrimination at the firm level.

Second, our study contributes to a vast literature in sociology and anthropology on the relation between globalization and national culture. Hofstede (1980) shows that national culture is multi-dimensional and therefore is determined by both internal and external forces. Pieterse (2003) and Hopper (2007) study how economic globalization can reshape the culture of those participating countries.[3] Most of these sociology and anthropology studies are either pure theories or case studies. Our paper provides more rigorous empirical evidence using a large-scale firm-level dataset. Our findings seem to lend a support of cultural convergence hypothesis. Recent studies in economics have started to examine specific channels through which cultural values can transfer from one country to another (Fisman and Miguel, 2007; Maystre et al., 2014).

Third, it is related to the economics literature on group discrimination. 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 market forces. But he also points out that this will not happen if all firms hold the same prejudice. Black and Brainerd (2004) test Becker's hypotheses by exploiting the varying degree of exposure to import competition across industries in the U.S. They find that competition due to trade liberalization is associated with a lower gender wage gap. Using Japanese firm-level data, Kawaguchi (2007) finds that the impact of gender discrimination on firm profit is small. Japanese firms that hire more women do not grow faster than those firms that hire fewer women.

Fourth, given that our project is about FDI, it is related to an extensive literature on FDI technology spillover to the host country economy (Aitken and Harrison, 1997; Javorcik, 2004). Research in economics has cumulated a rich stock of evidence about how economic globalization can facilitate cross-border transfer of knowledge, technology, and managerial knowhow. However, there is relatively scant evidence on the transfer of culture. Our study fills this void by studying whether and how FDI can serve as a vehicle to transfer culture from one country to another. We

[3] 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".

are able to add a cultural dimension to the FDI host country effect.

Finally, our project is naturally related to the growing economics literature on gender inequality in China (e.g., Qian, 2008; Kuhn and Shen, 2013; Chen et al., 2013; Edlund et al., 2013). 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 gender inequality, we will examine an important macroeconomic factor, FDI, and how it can affect the gender inequality.

The rest of the paper proceeds organized as follows. Section 2 describes our theoretical model. Section 3 discusses our data source, measurement issues and summary statistics. Based on our theory, Sections 4 and 5 test the gender cultural transfer and gender cultural spillover predictions. The last section concludes.

2 Model

2.1 Set-up

2.1.1 Preferences and Market Structure

We build a theoretical model to guide our empirical analysis. We outline the model here and relegate the full model with detailed derivations and proofs to the appendix. Our model features three layers: sectors, firms, and tasks. Consumers consume goods from a continuum of sectors, indexed by $j \in [0,1]$. Within a sector, firms produce horizontally differentiated varieties and face their own demands. The aggregate consumption bundle is set as the numeraire (i.e., we set its price level, $P = 1$). The model features heterogeneous firms, monopolistic competitive goods markets, and constant-elasticity-of-substitution preferences, as in Melitz (2003). Firms are heterogenous along two dimensions. Before entry, a firm draws productivity φ from a cumulative distribution function $G(\varphi)$. In addition, it draws a parameter for female discrimination from a different cumulative distribution function $H(\gamma)$, which is assumed to be independent from $G(\varphi)$. A firm with productivity φ has revenue equal to $R(A_j, \varphi) = A_j^{1-\eta} y(\varphi, \gamma)^{\eta}$, where A_j determines the level of demand in sector j, which is taken as given by each firm. $y(\varphi, \gamma)$ is the firm's output level that depends on productivity and the degree of discrimination.

2.1.2 Production

On the production side, we follow Acemoglu and Autor (2011) (AA hereafter). Each firm hires a continuum of tasks, indexed by $i \in [0,1]$. Specifically, the production function of sector j requires all task inputs and takes the following Cobb-Douglas form:

$$Y_j = \int_0^1 \beta_j (i) \ln y (i) \, di.$$

$\beta_j (i)$ captures how intensively task i is used to produce sector-j goods. To preserve the CRS property of the sector-level production function, we assume that

$$\int_0^1 \beta_j (i) \, di = 1.$$

Using the terminology of Pitt et al. (2012), each task i combines skills (S) and brawn (B) labor inputs linearly as follows

$$y (i) = \alpha_B (i) B (i) + \alpha_S (i) S (i) ,$$

where $\alpha_B (i)$ and $\alpha_S (i)$ capture the effectiveness of delivering a task using brawn and skills, respectively.

Without loss of generality, tasks are ranked in such a way so that a higher i indicates a more intensive use of of skills relative to brawn services in production. In addition, sectors are ranked in such a way so that a higher j indicates a more intensive use of skill-intensive tasks. In other words, skill intensity of a sector is defined by the skill intensities of the underlying tasks.

Similar to AA, we show in the appendix that wages for skill and brawn inputs are the same regardless of which sectors or tasks the inputs are being used. In equilibrium, high-i tasks use only skill as inputs while low-i tasks only brawn.

2.1.3 Labor Supply

On the labor supply side, the economy is endowed with two types of workers: males and females. Denote the mass of male workers and female workers by M and F, respectively. Each worker (female or male) is endowed with both skill 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).[4] In other words, female workers have a comparative advantage in skill-intensive tasks. As in AA, each worker has one unit of time and has to decide how to allocate the time used on supplying brawn or skills. In the appendix, we show that female workers will allocate all their time to supply skills,

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

while male workers will only supply brawn. The idea is that wages will adjust to reflect workers' comparative advantage, in the same manner prices adjust in the traditional Ricardian trade model. In equilibrium, both females and males will completely specialize in what they are relatively better at. We therefore obtain a one-to-one mapping between skill and female labor supply, and between brawn services and male labor supply. In other words, within each sector, high-i tasks are done by women while low-i tasks are done by men.

2.1.4 Firm Equilibrium

We solve for a firm's equilibrium employment ratio and profits in this section. Sector subscripts are suppressed to simplify notation. Consider a firm with productivity level, φ, and a discrimination parameter, γ. Under monopolistic competition with CES utility, the firm maximization problem becomes one that maximizes a Cobb-Douglas production function over male and female labor, taking both of their wages, as well as its own discrimination parameter, γ, as given. Following Becker (1957) and the subsequent studies, we model discrimination as taste-based and use γ to represent the amount of utility loss for the firm owner in terms of revenue units. More specifically, for each additional unit of women hired, the disutility for the firm owner is equivalent to γ units of revenue loss.

Specifically, a firm maximizes its objective function by choosing male (m) and female (f) employment as follows:

$$\pi\left(\varphi,\gamma\right)=\max_{f,m}\left\{A^{1-\eta}\left(\varphi\widetilde{\mu}f^{\beta}m^{1-\beta}\right)^{\eta}-\left(w_f+\gamma\right)f-w_m m\right\}$$

where $\widetilde{\mu}$ is a sector-specific parameter (see the appendix), w_f is the female wage rate, w_m is the male wage rate, and γ is the discrimination parameter.

Firms' maximization yields the following female-male employment ratio:

$$\frac{f}{m}=\frac{\beta}{1-\beta}\frac{w_m}{w_f+\gamma}.$$

$\frac{f}{m}$ is increasing in β, the average dependence on skill inputs. In the empirical section below, we can thus use the female-male employment ratio of a sector for a wide range of countries to proxy for female comparative advantage across sectors. Almost by definition, firms that discriminate more hire proportionately less female workers. More importantly, the gap between the female-male ratio and the optimal ratio when there is no discrimination, $\Delta\left(\frac{f}{m}\right)=\left(\frac{f}{m}\right)-\left(\frac{f}{m}\right)^{nd}$ is:

$$\Delta\left(\frac{f}{m}\right) = -\left(\frac{f}{m}\right)^{nd}\frac{\gamma}{w_f+\gamma}, \tag{1}$$

where $\left(\frac{f}{m}\right)^{nd}$ stands for the firm's optimal female-to-male ratio in the absence of discrimination (i.e., when $\gamma = 0$). Since the optimal level of female-male ratio is not observable in the data, we will not be able to test this prediction directly. However, if we have data of affiliates of multinational firms from different countries, we can empirically examine the following prediction implied by (1).

Prediction 1 (About female employment)

Firms from countries that discriminate female workers more have a smaller female-to-male ratio within an industry. The negative relationship is smaller if female wages are higher (e.g., higher skilled workers).

Substituting firms' optimal level of female and male workers into the definition of profit yields the following profit function:

$$\pi(\varphi,\gamma) = \Lambda\varphi^{\frac{\eta}{1-\eta}}\left(w_m^{1-\beta}(w_f+\gamma)^{\beta}\right)^{-\frac{\eta}{1-\eta}}, \tag{2}$$

where $\Lambda = (1-\eta)\left(\mu\beta^{\beta}(1-\beta)^{1-\beta}\right)^{\frac{\eta}{1-\eta}}$ is a constant that depends on sector-specific parameters (see the appendix for details). Given $\frac{\partial \ln \pi(\varphi,\gamma)}{\partial\gamma} < 0$, we have the following testable hypothesis.

Prediction 2 (About TFP loss)

Firms that discriminate female workers more have a smaller measured total factor productivity, all else being equal.

Two firms with the intrinsic TFP, φ, will have different measured TFP. Our model emphasizes that it arises from discrimination, although in reality, there can be many sources of distortion that deliver similar results.

2.2 Cultural Spillover

The way that we empirically examine cultural transfer and cultural spillover is based on the variation in γ across foreign firms from different countries. According to Prediction 1, countries that have a culture that treat women more favorably will employ relatively more female workers, all else being equal. Do multinational firms transfer their culture to their affiliates overseas? We will provide empirical evidence this below. Another intuitive conjecture based on Prediction 1 is that to the extent that foreign investors have more control over employment decisions in wholly-owned affiliates than joint ventures, wholly-owned affiliates for a source country that has a lower gender bias should have a lower female-to-male ratio. We will also verify this prediction below.

Besides cultural transfer, do multinational affiliates influence domestic firms to hire more women? In other words, are there cultural spillover from FDI in addition to technology spillover that has been well documented in the literature? When foreign firms enter a sector (city), they will drive up wages. Higher wages imply lower profits for all. To reduce profit loss, firms will reduce their discrimination. This is particularly true for the least productive firms who are concerned about survival. In this sense, a positive correlation between domestic firms' female employment ratio and the prevalence of overall FDI simply suggests that there is no spillover. Firms adjust their female employment ratio in responses to competitive pressure, as proposed by Becker (1957) and the subsequent empirical studies. We thus have the following proposition.

Prediction 3 (Heterogeneous responses)

Firms that are ex-ante less productive choose to reduce discrimination by more, in response to increased FDI flows in the same sector or city.

Based on firms' ex-ante TFP, we can verify this claim in the empirical section.

To show that FDI generates cultural spillover, we need to look into FDI's countries of origin, not only its overall volume. We model cultural spillover in reduced form. To fix idea, we now assume that a firm's discrimination parameter depends on not only the firm's own discrimination parameter, but also foreign firms in the same sector (city). Specifically, we assume that the adapted discrimination parameter of the firm takes the following form:

$$\gamma\left(n, \widetilde{\gamma}\right) = \gamma^{1-\delta(n)} \widetilde{\gamma}^{\delta(n)}. \tag{3}$$

where $\widetilde{\gamma}$ is the average discrimination factor of foreign firms in the same sector (province). $\delta\left(n\right)$ is the weight the firm would put on this average parameter in changing its own ex-post discrimination factor, and n is the number of foreign firms. To capture the intuitive idea that the firm is more likely to be influenced if there are more foreign firms in the sector, we assume that $\delta'\left(n\right) > 0$. Since

$$\frac{\partial \ln \gamma\left(n, \widetilde{\gamma}\right)}{\partial n} = \delta'\left(n\right) \ln\left(\frac{\widetilde{\gamma}}{\gamma}\right) > 0 \text{ if } \widetilde{\gamma} > \gamma, \tag{4}$$

domestic firms' female employment increasing in n as well because of Prediction 1.

The key question is how to separate the competition effect from the imitation effect? The details can be analyzed based on the complementary effect between n and $\widetilde{\gamma}$. Simple comparative static shows that

$$\frac{\partial \ln \gamma \left(n, \widetilde{\gamma}\right)}{\partial n \partial \widetilde{\gamma}} = \frac{\delta' \left(n\right)}{\widetilde{\gamma}} > 0, \tag{5}$$

and thus, domestic firms respond by increasing female employment if foreign firms in the same sector are from countries with less discrimination. Notice that if it is solely because of the competition effect where we find spillover, we will find evidence supporting the comparative static (4) but not (5). We will thus empirically examine the following prediction.

We can further show that the spillover effect differs across sectors. In particular, the stronger the female comparative advantage in the sector is, the larger the spillover effect. It can be illustrated by the following comparative static for a given firm:

$$\frac{\partial \left(\frac{f}{m}\right)}{\partial \beta \partial \widetilde{\gamma}} > 0.$$

Prediction 4 (Cultural spillover)

Domestic firms' female employment ratio is increasing in the prevalence of FDI in the same sector or city that are on average less discriminating than Chinese firms. The spillover effect will be stronger the larger the gender bias gap between Chinese firms and foreign firms, or the stronger the female comparative advantage in the sector is, given the same level of FDI.

3 Data, Measures and Summary Statistics

3.1 NBS Above-Scale Firm-Level Database

The primary data set for our study comes from China's National Bureau of Statistics (NBS) "above scale" industrial firm surveys, conducted annually over the 2004-2007 period. This dataset covers all state-owned firms, and non-state firms that have sales above 5 million RMB (about 0.7 million USD at 2007 exchange rate). The data contain detailed balance sheet information of firms, such as output, value added, industry code, exports, employment, intermediate inputs, as well as their addresses and ownership type based on registration. In 2004, firms in our dataset accounted for 91 percent of China's gross industrial output, 71 percent of employment, 97 percent of exports, and 91 percent of total fixed assets. To create a panel data set, we use firm ID to identify and link the same firm across years. However, a firm's ID may change possibly due to restructuring or merger and acquisition. To link firms over time, in addition to using firm IDs, we also use information on firms' name, sector, and address.

Most importantly, we use the following firm-level variables related to gender from the data set in our analysis:

1. For 2004, we have information of firm employment breakdown by gender and education.[5]

2. For 2005, 2006, and 2007, we only have employment breakdown by gender.

In this paper, a worker is considered as skilled if she has education of senior high school or above. Based on this definition, 39 percent of total employment in our data set are skilled in 2004.[6]

Notice that our data do not provide a wage breakdown by gender. With this limitation, we can only study employment gender inequality, but not wage inequality, at the firm level. Consequently, we can only study skill structure based on employment share, rather than wage share.

In the empirical analysis, we use firm's registration type information to identify foreign invested firms. To measure firm performance, we estimate firm TFP using Olley-Pakes procedure.

3.2 Ministry of Commerce FDI Survey Database

The NBS firm-level dataset does not provide information of foreign investors' country of origin. To solve this problem, we obtain country of origin data from China Ministry of Commerce Foreign Invested Firms Survey database. The Ministry of Commerce (MOC) conducted several waves of survey of all foreign invested firms in China. We merge the MOC country of origin data with the NBS firm data using firm name and contact information. About 52% of the 2004 foreign invested firms (excluding Hong Kong, Macau and Taiwan firms) in the NBS data can be merged with the MOC FDI survey data.

3.3 Measures of Country-Level Gender-Related Culture

To measure country-level gender-related culture, we use two sets of data:

3.3.1 UNDP Gender Inequality Index

The most commonly used data in cross-country gender studies is the UNDP Gender Inequality Index (GII). It is a composite measure which captures the loss of achievement due to gender inequality. This index focuses on three dimensions: reproductive health, empowerment, and labor

[5] 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.

[6] 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.

market participation. A higher value indicates greater gender inequality. We use the 2012 Gender Inequality Index, which covers 149 countries. Countries with lowest GII are Netherlands, Sweden, Switzerland, Denmark and Norway. Countries with highest GII include Yemen, Afghanistan, Niger, Saudi Arabia and Congo. Obviously, GII correlates with national income level. But there are countries with high income level that score very high in GII (such as Saudi Arabia) and countries with both low income and low GII (such as the Philippines).

3.3.2 World Value Survey

As a robustness check, we supplement the GII index with the data from World Value Survey (WVS), which is a direct and subjective measure of gender-related values and beliefs. We use the 2005 wave of WVS, which contains data from 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", and 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. Then 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, countries with the highest WVS scores are Egypt, Jordan, Mali, India and Afghanistan. The five lowest WVS score countries are Sweden, Norway, Andorra, France and Finland.

Unfortunately, GII and WVS do not provide gender inequality measures for Hong Kong and Taiwan, two of the largest investors in China.

3.4 Legal Person Representatives

Gender inequality might be greater at the higher level within the organization of the firm. This is often referred to as the "glass ceiling effect," which prevent females from taking high-level management positions (Nevill et al., 1990). Does gender cultural transfer also affect firms' selection of female managers? In other words, were foreign parent firms from countries with greater gender equality more likely to employ women as the managers of their affiliates? To answer these questions, we take advantage of the information of legal person representatives in our data. Unfortunately, we only have their names but not the gender information of these legal person representatives. To solve this problem, we come up with a novel way that relies on the last character of the representatives' Chinese names to infer their gender. This can be done as long as we can find a systematic method to identify feminine versus masculine names.

To measure the femininity (masculinity) of a name, we take advantage of a random sample of China's 2005 1% population survey. We construct a database with 2.5 million names and gender information. Since parents' taste of giving names to their children often change over time, to make the average age comparable to the legal person representatives of the firms, we further restrict our sample to the people who were aged between 35 and 65 in 2005. The first two columns of Appendix Table A1 list ten most frequently used Chinese characters that appear as the last characters of the female and male names.

For each Chinese character, we calculate the probability that it is a female name based on our name database, using the following formula:

$$female\_prob_i = \frac{frequency\_female_i}{frequency\_female_i + frequency\_male_i}, \tag{6}$$

where $frequency\_female_i$ ($frequency\_male_i$) is the number of times that character i appears as the last character in a female (male) name. The last two columns of Appendix Table A1 report the Chinese characters with the highest $female\_prob$ and lowest $female\_prob$.

3.5 Summary Statistics

Table 1 reports summary statistics of the 2004 data. Average female employment share of the FIEs (excluding Hong Kong, Macau and Taiwan firms) is 0.479, which is much higher than that of the Chinese firms (0.397). FIEs also have higher probability to hire women as legal person representatives. Next we split the FIEs countries of origin into two groups, those with GII higher than China and those with GII lower than China. Surprisingly, Table 1 shows that compared to Chinese local firms, even the FIEs from countries with GII higher than China have a higher female employment share (0.454) and higher female probability of legal person representatives (0.246) than Chinese firms. There are several possible explanations: First, there may be a selection bias. Those FIEs from high GII countries may not be the ordinary firms in their home countries. Second, after the FIEs from high gender inequality countries invest in China, they may have to change and learn in order to compete in the Chinese market. Third, FIEs could be the targets of Chinese government labor law enforcement. It is possible that, compared to Chinese firms, all FIEs regardless of their country of origin are less likely to break the law.

From Table 1's 2004 data summary statistics, we see FIEs' significant advantage in female share in employment and female probability of legal person representative. In table 2, using the panel data of 2004-2007, we run some regressions with FDI dummy as an independent variable. The omitted group is the Chinese local firms. Column (1) of Panel A shows that the FIEs' female share of employment is on average 7.6 percentage points higher than the Chinese firms. The coefficient of column (2) is smaller when industry and provincial fixed effects are controlled for. This is because FIEs are more concentrated in those industries and provinces with higher female employment share. The third column controls firm fixed effect. The identification only comes from the firms that switched the ownership between the FIEs and the local firms. The coefficient indicates that a foreign investor would increase female share by 2 percentage points in the first year after it acquired a Chinese local firm. Columns (4)-(6) study two types of FDI: those from countries with GII higher than China and those with GII lower than China. We can see that both the high GII FDI and the low GII FDI treat women more equally than Chinese local firms. Panel B reports the results of the same regressions, but we use $female\_prob$ as the dependent variables. The results are generally similar to those in Panel A.

4 Estimating the FDI Gender Cultural Transfer to Chinese Subsidiaries

To investigate the gender cultural transfer from foreign parent firms to their Chinese subsidiaries, we estimate the following specification using the 2004 data:

$$S_{ij} = \beta_0 + \beta_1 GII_j + \beta_2 income_j + \mathbf{X}'_{ij}\boldsymbol{\gamma} + \{FE\} + \varepsilon_{ij}, \tag{7}$$

where S_{ij} is the share of female workers or female probability of legal person representative of firm i with foreign country of origin j. GII_j is a measure of gender inequality for country j. $income_j$ is log GDP per capita of country j. $\mathbf{X}_{ij}$ is a vector of firm i's characteristics, which include the firm's computer intensity, R&D intensity, skill intensity, and logarithms of TFP, capital intensity, output, wage rate and firm age. See Appendix Table 2 for the definitions of all variables and sources of the data. $\{FE\}$ stands for four-digit industry fixed effects and provincial fixed effects. ε_{ij} is the error term.

The challenge in the empirical test is to control for the confounding factors. In equation (7) we include home country GDP per capita to control other potential influences from the home countries. We also include several firm characteristics and industry fixed effects to control firm-level and industry-level factors that may affect female share in total employment. Moreover, China's social and legal environment differs significantly across regions. Local labor institutions and local labor supply are major determinants of female employment. We include a full set of provincial fixed effects to control for time-invariant unobservable heterogeneity across regions. Our sample in these regressions includes all FIEs.

Table 3 reports the regression results. In column (1), GII is negative and statistically significant at the 1% level, which is consistent with the first part of Prediction 1 that greater gender inequality in FDI home country is associated with lower female share in firm's total employment. Based on the estimate in column (1), we can calculate the quantitative significance of GII. A one-standard-deviation increase in GII is associated with about 2.5 percentage point decrease in female share in total employment. Home country's income level has no effect on female share as log GDP per capita is statistically insignificant in Table 3. Computer intensity, R&D intensity, TFP and wage rate all have negative impacts. An obvious difference between Chinese local firms and the FIEs is the technology. But technology cannot explain the higher female share in these FIEs. In fact, if the FIEs have higher technology, they should have smaller share of female labor since Table 3 shows a clear negative relation between technology and female share.

In the first few years after foreign firms invested in China, the FIEs may bring the culture from their home country. However, overtime such foreign culture may be influenced by or assimilated into Chinese local culture. As a result, these FIEs would adapt to the Chinese cultural environment and behave more like Chinese local firms. If this is the case for the gender culture, we would expect to see a negative relationship between female share and firm age. Our estimation results in Table 3 do not support this assimilation hypothesis, since the coefficient of firm age is positive and statistically significant in columns (1) and (5), and positive but insignificant in other columns.

In columns (2) and (3), we change the dependent variable to investigate whether there are different cultural transfer effects between the skilled labor and the unskilled labor. The estimation results show that GII has a negative sign in both columns (2) and (3), but the coefficient of GII is larger in column (2), indicating that the gender cultural transfer effect is stronger for the unskilled labor. To the extent that skilled labor have higher wages, this finding supports the second part of Prediction 1. Skilled intensity helps increase female share in the skilled labor but adversely affects it in the unskilled labor. This may explain why skill intensity is not statistically significant when skilled and unskilled labor is combined in column (1).

The FDI cultural transfer not only depends on foreign parent firms' home country's culture, but also depends on foreign parent firms' control over its Chinese subsidiaries. We consider the following measure of parent firms' control: wholly-owned FIEs vs. joint ventures. Our hypothesis is that wholly owned foreign invested firms are more likely to transfer home country's gender culture than joint ventures. In column (4) of Table 3, we add an interaction term between GII and joint venture dummy. The coefficients of the interaction term is positive and significant, supporting our hypothesis that parent firm's control also matters in the gender cultural transfer.

Next, we change our dependent variable to female probability of legal person representatives. Column (5) of Table 3 reports a negative and significant correlation between GII and the probability that the legal person representative is female. Our findings suggest that home country of FDI source is associated with cultural transfer that affects not only employment of female workers, but also the appointment of females at the top of the firm.

As a robustness check, in column (6) we use an alternative measure of country gender culture – World Value Survey score – as an independent variable. The regression results are generally consistent with those in column (1).

5 Estimating the FDI Gender Cultural Spillover to Chinese Local Firms

We begin this section by testing Prediction 2 of the model. To investigate the relationship between firm productivity and its gender inequality, we regress ln(TFP) on female share and other control variables using the 2004-2007 data. As we can see from Table 4, the first column shows a negative and significant sign for female share. But the coefficient of female share turns positive and significant when we control firm fixed effects. To the extent that controlling firm fixed effects eliminates the bias brought by unobservable firm heterogeneity, our results support Prediction 2 that less prejudice against women at the firm level contributes to firm productivity. [7]

Next, we test Prediction 4 of the model about the gender cultural spillover from FIEs to Chinese local firms. Again, we use female share in total employment and the probability of female legal person representative as the measures of gender inequality. A majority of empirical studies of FDI technology spillover have adopted a reduced form estimation (e.g., Aitken and Harrison, 1997; Javorcik, 2004). We follow this approach and estimate the following equation:

$$S_{ik} = \beta_0 + \beta_1 FDI\_presence_k + \mathbf{X}'_{ik}\gamma + \{FE\} + \varepsilon_{ik}, \tag{8}$$

where S_{ik} is the share of female workers or female probability of legal person representative of firm i in four-digit industry k. $FDI\_presence_k$ is FIE's share of output in industry k. $\mathbf{X}_{ik}$ is

[7] Note that gender cultural spillover may not depend on the assumption that reducing gender bias increases firm productivity. Learning the new values from the FIEs, Chinese local firms may find it inappropriate to discriminate women, regardless of the productivity effects.

a vector of the same firm characteristics in equation (7), including the firm's computer intensity, R&D intensity, skill intensity, and logarithms of TFP, capital intensity, output, wage rate and firm age. $\{FE\}$ represents a full set of provincial fixed effects.

Our theoretical model shows that FIEs can affect local firms' female employment share through competition effect and imitation effect. The imitation effect can be technology imitation or cultural imitation. The technology imitation or FDI technology spillover can be gender-biased. For instance, it has been shown in the literature that the adoption of computer significantly increases the demand for female labor. Since FDI is often associated with technology transfer to local firms, such transfer or imitation could affect Chinese local firms' gender employment ratio, especially if the technology is gender-biased. The imitation of culture, or the cultural spillover, is the focus of our paper. Different from the competition effect or technology transfer effect, FDI may change the gender employment ratio by changing the gender value or preference of Chinese local firms. To identify the cultural spillover, we include Herfindahl index and R&D to control for the potential channels of competition effect and gender biased technology spillover effect.

We first estimate equation (8) with all Chinese local firms in 2004. According to the results reported in the first three columns of Table 5, foreign presence is positive and significant, which is consistent with the first part of Prediction 4. Comparing columns (2) and (3), we can see that the gender spillover effect is stronger for the unskilled labor.

In column (4), we measure FDI presence with two variables: FDI from countries with GII higher than China and FDI from countries with GII lower than China. We find that although both of the two FDI presence measures increase Chinese local firms' female share in total employment, FDI presence from low GII countries has a larger spillover effect. Note that the FDI presence from countries with gender inequality greater than China, can still increase Chinese local firms' female share. This is not too surprising given the fact that even FIEs from high gender inequality countries on average have higher female share than Chinese firms (Table 1 and Table 2).

In column (5), we include an interaction term between FDI presence and industry female comparative advantage. The data of industry female comparative advantage come from Do, Levchenko and Raddatz (2014), who compiled the female share in employment at the industry level using the data from a wide range of countries.[8] The interaction term is positive in column (4), suggesting that FDI spillover effect is stronger in those industries that traditionally hire more women. In summary, we find evidence of the second part of Prediction 4 that the spillover effect is stronger the larger the gender bias gap between Chinese and foreign firms (supported by column 4 results) or the stronger the female comparative advantage in the sector is (supported by column 5 results).

[8] Do, Levchenko and Raddatz compiled the data using ISIC industries. We create a concordance table between ISIC and Chinese industry classification.

Column (6) of Table 5 uses $female\_prob$ as the dependent variable. The coefficient of FDI presence is much smaller, but it is still statistically significant at the 1% level.

Since physical distance may matter for cultural spillover, the last column of Table 5 uses an alternative measure of FDI presence - the FDI output share in the same city, instead of the same industry. The estimation results are qualitatively similar to those in column (1).

It is important to control firm unobservable heterogeneity in the spillover regressions. In Table 6, we report firm fixed effect regression results using the 2004-2007 panel data. In the first column of Table 6, FDI presence in industry is still positive and significant, but the size of the coefficient is only about one tenth of our result reported in the first column of Table 5. Such difference highlights the importance of controlling for firm fixed effects. In column (2), we include FDI from high GII countries and FDI from low GII countries. The results are consistent with our earlier findings in Table 5. In column (3), we add an interaction term between FDI presence and industry-level female comparative advantage. The interaction term is negative and significant, again, similar to the results in Table 5.

Column (4) of Table 6 tests Prediction 3 that firms that are ex-ante less productive choose to reduce discrimination more when facing FDI inflow. We include the interaction term between FDI presence and firm's lagged productivity. The negative and statistically significant coefficient of the interaction term shows that FDI cultural spillover has a stronger effect on less productive firms, supporting our model Prediction 3. The last column of Table 6 reports the positive and significant spillover effect from the FDI in the same city, an alternative measure of FDI presence.

6 Concluding Remarks

This paper examines whether and how FDI may change the gender culture of Chinese local firms. We utilize a comprehensive manufacturing firm-level survey from China National Bureau of Statistics over 2004-2007. We develop a model of multi-sector task-based model that features heterogeneity in firm productivity and degree of biases towards female workers. Our empirical results support the theoretical predictions. Based on country-level gender inequality indices, we show that FIEs from a country with lower gender inequality tend to hire more female workers, and are also more likely to hire women as their managers. Our estimation results are robust to the inclusion of control variables such as home country income, firm productivity, skill intensity and R&D intensity. We also find that Chinese firms' female share is positively correlated with the prevalence of FDI in the same industry. Such cultural spillover effect is stronger for FDI from countries with lower gender inequality, for firms that are ex-ante less productive, and in industries where women have a comparative advantage. Our results suggest that in addition to technology transfer and spillovers that have been documented in the literature, FDI may be an important vehicle to diffuse culture across countries.

In sum, this paper highlights how globalization can overturn the long-run prejudice against women via economic forces. In this regard, our paper 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, and tasks employed by firms. There is a continuum of sectors, indexed by $j \in [0,1]$. Consider consumers with identical preferences over a continuum of products: $U = \left[\int_0^1 C_j^{\nu} dj\right]^{\frac{1}{\nu}}$, where $\kappa \equiv 1/(1-\nu) > 1$ is the elasticity of substitution between products. Within a product, firms produce horizontally differentiated varieties, facing their own demand. The consumption index for product j, C_j, takes the following form:

$$C_j = \left[\int_{\omega \in \Omega_s} c_j(\omega)^{\eta} d\omega\right]^{\frac{1}{\eta}}, \ 0 < \rho < 1, \tag{9}$$

where $\sigma \equiv 1/(1-\eta) > 1$ is the elasticity of substitution between varieties within a sector. We assume that the elasticity of substitution between varieties within a product is larger than that between products ($\sigma > \kappa > 1$). Each variety is produced by a firm.

Let $p_j(\omega)$ denotes the price of variety ω within the sector. The price index of the sector j, $P_j = \left[\int_{\omega \in \Omega_s} p_j(\omega)^{1-\sigma} d\omega\right]^{\frac{1}{1-\sigma}}$. The consumer price index of the economy is thus $P = \left[\int_0^1 P_j^{1-\kappa} dj\right]^{\frac{1}{1-\kappa}}$. We set the aggregate consumption bundle as the numeraire (setting $P = 1$).

The model features heterogeneous firm productivity, monopolistic competitive goods markets, and constant-elasticity-of-substitution 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 $G(\varphi)$. It also draws a parameter for female discrimination, from a different cumulative distribution function $H(\gamma)$. Specifically, consider a firm with productivity φ. Its revenue will be $\pi^{o}(A,\varphi) = A^{1-\eta} y(\varphi)^{\eta}$, where A determines the level of demand, taken as given by each firm, and $y(\varphi)$ is the output level that depends on productivity, φ.

A.1.2 Production

On the production side, we follow Acemoglu and Autor (2011) (AA hereafter). Each firm hires a continuum of tasks, indexed by $i \in [0,1]$. Output of sector j requires possibly all task inputs, which for simplicity is described by the following production function:

$$Y_j = \int_0^1 \beta_j(i) \ln y(i)\, di$$

The importance of task i in the production of j is captured by a continuous measure of weights, $\beta_j(i)$. Consider two sectors, j and j', if $\beta_{j'}(i) > \beta_j(i)$, task i is used more intensively in the production of sector-j goods. To preserve the CRS property of the sector-level production function, we assume that

$$\int_0^1 \beta_j(i)\, di = 1.$$

Each task i combines skills (S) and brawn (B) labor inputs linearly as follows

$$y(i) = \alpha_B(i) B(i) + \alpha_S(i) S(i).$$

In words, skills and brawn are assumed to be perfectly substitutable. $\alpha_B(i)$ and $\alpha_S(i)$ capture the effectiveness of delivering a task using brawn and skills, respectively.

Now let us make two ranking assumptions. First, without loss of generality, we rank tasks in such a way to impose the structure of comparative advantage in the model as follows:

Assumption 1:
$\alpha_S(i)/\alpha_B(i)$ is continuously differentiable and strictly increasing in i.

In other words, skill inputs are more effective in delivering a high-i task. Second, we rank sectors such that a higher sector index j requires on "average" higher skill inputs. To this end, we make the following assumption:

Assumption 2:
Sectors are ranked in such a way so that $\int_0^k \beta_{j'}(i)\, di > \int_0^k \beta_j(i)\, di$ for all $k < [0,1)$ if $j > j'$.

Notice that the idea behind this inequality is similar to the concept of first order stochastic dominance. A stronger version of this assumption is that $\frac{d\beta_{j'}(i)}{di} \geq \frac{d\beta_j(i)}{di}$ for all $i < [0,1]$ if $j > j'$. In that case, the weights, $\beta_j(i)$ is increasing in i faster than that in $\beta_j'(i)$, or high-i tasks are becoming increasingly more important.

Before turning to the comparative advantage and labor supply decisions of different genders, let us describe the labor demand side, in particular, firms' demand for skills and brawn for each task. Similar to AA, we can derive the following proposition regarding the use of skills and brawn demand for each task.

Proposition 1 *There exists a threshold i_j^* for each sector j such that all firms within the sector will use brawn inputs for all tasks $i \leq i_j^*$ and skill inputs for all tasks $i > i_j^*$.*

Proof. The formal proof of this lemma can be found in Acemoglu and Zilibotti (2001). The main idea behind the proof is intuitive. Given wages for both inputs, w_B and w_S, consider the cutoff task i_j^*. One unit of $y\left(i_j^*\right)$ can be done at the same cost by using skills only, which costs $\frac{w_B}{\alpha_B(i^*)}$, or brawn only, which costs $\frac{w_S}{\alpha_S(i^*)}$. Given Assumption 1, $\frac{w_S}{\alpha_S(i)} < \frac{w_B}{\alpha_B(i)}$ for all $i > i_j^*$. In other words, it is strictly less costly to produce any tasks with $i > i^*$ using skills only rather than brawn only or a mix of the two. ■

A.2 The law of one price of skills

Owners of skills and brawn are free to switch tasks and sectors. Thus, wages for both types of skills follow the law of one price. Specifically, the following wage equations should hold

$$\begin{aligned} w_B &= p_j\left(i\right)\alpha_B\left(i\right) \text{ for all } i < i_j^* \text{ and all } j \\ w_S &= p_j\left(i\right)\alpha_S\left(i\right) \text{ for all } i < i_j^* \text{ and all } j, \end{aligned}$$

where $p_j\left(i\right)$ is the price of task i used in sector j. In other words, given constant w_B, w_S, $\alpha_B\left(i\right)$, and $\alpha_S\left(i\right)$, $p_j\left(i\right)$ will adjust in such a way to make sure that the above equations will hold.

Given the Cobb-Douglas production function for each sector j, firms' demand for each type of skills can be pinned down as follows

$$p_j\left(i\right)\alpha_B\left(i\right)l_j\left(i\right) = \beta_j\left(i\right)TVC \text{ for any } i \text{ and } jm$$

where TVC stands for total variable cost.

Thus, for any two tasks that use brawn services

$$\frac{p_j\left(i\right)\alpha_B\left(i\right)B_j\left(i\right)}{\beta_j\left(i\right)} = \frac{p_j\left(i\right)\alpha_B\left(i'\right)B_j\left(i'\right)}{\beta_j\left(i'\right)}$$

Given constant w_B and w_S across tasks, we have

$$\frac{B_j\left(i\right)}{\beta_j\left(i\right)} = \frac{B_j\left(i'\right)}{\beta_j\left(i'\right)}$$

Similarly, for any two tasks that use skills, the demand for skilled inputs satisfies:

$$\frac{S_j\left(i\right)}{\beta_j\left(i\right)} = \frac{S_j\left(i'\right)}{\beta_j\left(i'\right)}.$$

Given firm-level total brawn and skills, the split of the inputs implies

$$\begin{aligned} B_j\left(i\right) &= \frac{\beta_j\left(i\right)B_j}{\beta_j} \text{ for all } i \leq i_j^* \\ S_j\left(i\right) &= \frac{\beta_j\left(i\right)S_j}{1-\beta_j} \text{ for all } i > i_j^*, \end{aligned}$$

where $\beta_j = \int_0^{i_j^*} \beta_j\left(i\right)di$.

A.3 Labor Supply

Let us now turn to the labor supply side of the model. The economy is endowed with two types of workers: males and females. Let us denote the mass of male workers and female workers by M and F, respectively. Each worker (female or male) is endowed with both 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).[9] In other words, male 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

$$\frac{\theta_m^S}{\theta_m^B} > \frac{\theta_f^S}{\theta_f^B}. \tag{10}$$

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. Thus, the supplies of skills and brawn in the aggregate economy are endogenous. We will see clearly how each of them As such, each 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.

As we have shown above, the wage rate for one unit of skill supply and respectively for one unit of brawn, is the same regardless of which task or sector it is used. All males will choose B 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 S 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 (10), 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*

[9] 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.

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 (10), $\frac{\theta_m^S}{\theta_m^B} \leq \frac{w_B}{w_S}$ 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.4 Firm equilibrium

In this section, we focus on solving the firm's equilibrium. Sector subscripts are suppressed for simplicity. Each firm draws a total factor productivity φ from a and discrimination parameter γ. Under monopolistic competition with CES utility as specified above, the firm maximization problem is

$$\pi(\varphi,\gamma) = \max_{y(i)} \left\{ A^{1-\eta} \left[\varphi \int_0^1 \beta(i) \ln y(i)\, di \right]^\eta - \int_0^1 p(i)\, y(i)\, B_i di - \gamma f \right\}$$

where γ is the distaste for the level of female employment, f.

Based on Proposition 1, for all tasks $i \geq i^*$, only skill inputs will be used, while for all tasks $i < i^*$, only brawn inputs will be used. Together with the above lemma, we have the following corollary.

Corollary 1 *Only female workers will be hired to do tasks $i \geq i^*$; while only male workers will be hired to do tasks $i < i^*$.*

We can thus rewrite the maximization problem as:

$$\pi(\varphi,\gamma) = \max_{S,B} \left\{ A^{1-\eta} \left(\varphi \mu_S \mu_B S^\beta B^{1-\beta} \right)^\eta - w_B B - w_S S - \gamma f \right\}$$

where $\mu_B = \prod_{i=0}^{i^*} \alpha_B(i)^{1-\beta(i)}$ and $\mu_S = \prod_{i=i^*}^{1} \alpha_S(i)^{\beta(i)}$, and $\beta = \int_{i^*}^1 \beta(i)\, di$.

Given that there's no other intrinsic differences between workers beside gender, all female workers supply skills and get the same wage rate. Specifically,

$$w_f = w_S\theta_f^S \ \forall i \geq i^*,$$

where i^* is defined in Proposition 1.

Similarly, the wage rate for male workers is

$$w_m = w_B\theta_m^B \ \forall i < i^*.$$

The maximization problem can be further rewritten in terms of female and male labor as

$$\pi(\varphi,\gamma)=\max_{f,m}\left\{A^{1-\eta}\left(\varphi\mu f^{\beta}m^{1-\beta}\right)^{\eta}-(w_f+\gamma)f-w_m m\right\} \tag{A-1}$$

where $\mu=\prod_{i=0}^{i^*}\left(\frac{\alpha_B(i)}{\theta_m^B}\right)^{\beta(i)}\prod_{i=i^*}^{1}\left(\frac{\alpha_S(i)}{\theta_f^S}\right)^{\beta(i)}$, $\beta=\int_{i^*}^{1}\beta(i)\,di$, and $w_m=w_B\theta_m^B$ and $w_f=w_S\theta_f^S$.

Firms' maximization subject to monopolistic competition and perfectly competitive market yields the following female-male employment ratio:

$$\frac{f}{m}=\frac{\beta}{1-\beta}\frac{w_m}{w_f+\gamma}.$$

$\frac{f}{m}$ is increasing in β, the average dependence on skills. Almost by definition, firms that discriminate more hire proportionately female workers.

The gap between the female-male ratio and the optimal ratio when there is no discrimination, $\Delta\left(\frac{f}{m}\right)=\left(\frac{f}{m}\right)-\left(\frac{f}{m}\right)^{nd}$ is:

$$\Delta\left(\frac{f}{m}\right)=-\left(\frac{f}{m}\right)^{nd}\frac{\gamma}{w_f+\gamma},$$

where $\left(\frac{f}{m}\right)^{nd}$ is stands for the firm's optimal female-male ratio in the absence of discrimination (i.e., when $\gamma=0$).

Proposition 2 *Given a fixed level of discrimination, the deviation in the female-male ratio from the optimal when there is no discrimination is increasing in the female dependence of the sector (i.e, β), and is decreasing in the female wage rate w_f.*

Substituting the levels of female and male workers that maximize eq. (A-1) yields the following profit function:

$$\pi(\varphi,\gamma)=\Lambda\varphi^{\frac{\eta}{1-\eta}}\left(w_m^{1-\beta}(w_f+\gamma)^{\beta}\right)^{-\frac{\eta}{1-\eta}},$$

where $\Lambda=(1-\eta)\left(\mu\beta^{\beta}(1-\beta)^{1-\beta}\right)^{\frac{\eta}{1-\eta}}$ is a constant that depends on sector-specific parameters. Given $\frac{\partial\ln\pi(\varphi,\gamma)}{\partial\gamma}<0$, we have the following testable hypothesis. Two firms with the intrinsic TFP, φ, will have different measured TFP. Our model proposes that it arises from discrimination, although in reality, there can many sources of distortion that delivers similar results.

Notice that the negative effects of discrimination on firm productivity differs across sectors, as $\frac{\partial\ln\pi(\varphi,\gamma)}{\partial\gamma\partial\beta}<0$. Quite intuitively, sectors that are more skill-intensive, or female-dependent, will suffer from a larger productivity loss due to discrimination. We will empirically verify the following proposition:

Proposition 3 *Firms that discriminate female workers more have smaller measured total factor productivity, all else being equal. The negative effect of discrimination is larger if the sector in which the firm operates is more female-dependent.*

A.5 Cultural Transfer and Spillover

The way that we analyze cultural transfer and cultural spillover are that γ are different. Assume that foreign affiliates, especially the wholly-owned foreign firms that foreign investors have more control over employment decisions, γ will be lower. We can verify this in the empirical analysis.

More importantly, the female employment ratio can rise due to (1) selection; (2) competition; and (3) taste change. While we will leave the analysis on selection for future research, we focus on the last two effects in this paper.

When foreign firms enter the same sector (or city), they will drive up wages. Higher wages force the least productive firms to exit. Some of the firms will need to exit even they reduce discrimination to zero. Others have a choice to reduce discrimination to avoid exit. We thus have the following proposition.

Proposition 4 *Firms that are ex-ante less productive reduce discrimination by more, in response to increased FDI flows in the same sector.*

We model cultural spillover in reduced form. Specifically, we now assume that the taste parameter for women is a Cobb-Douglas aggregate of the firm's original taste parameter as follows:

$$\gamma\left(n, \widetilde{\gamma}\right) = \gamma^{1-\delta(n)} \widetilde{\gamma}^{\delta(n)}. \tag{11}$$

where $\widetilde{\gamma}$ is the average discrimination parameter of foreign firms in the locality (sector or province). $\delta\left(n\right)$ is the weight the firm would put on this foreign in changing its own ex-post discrimination parameter. It can be interpreted as an imitation parameter. We assume that $\delta'\left(n\right) > 0$, implying that the imitation is increasing in the prevalence of foreign firms.

The key question is how to separate competition effect from imitation effect? The details can be analyzed based on $\gamma\left(n, \widetilde{\gamma}\right)$. Notice that complementing the competition effect due to increasing wages, we have

$$\frac{\partial \ln \gamma\left(n, \widetilde{\gamma}\right)}{\partial n} = \delta'\left(n\right) \ln\left(\frac{\widetilde{\gamma}}{\gamma}\right) > 0 \text{ if } \widetilde{\gamma} > \gamma$$

$$\frac{\partial \ln \gamma\left(n, \widetilde{\gamma}\right)}{\partial n \partial \widetilde{\gamma}} = \frac{\delta'\left(n\right)}{\widetilde{\gamma}} > 0.$$

Proposition 5 *The spillover effect is stronger if there are more foreign firms in the same sector that are on average less discriminating than Chinese firms. The effect will be stronger the larger the gender bias gap between Chinese and foreign firms is, given the same level of foreign presence.*

Figure 1: An Empirical Framework of Gender Cultural Diffusion

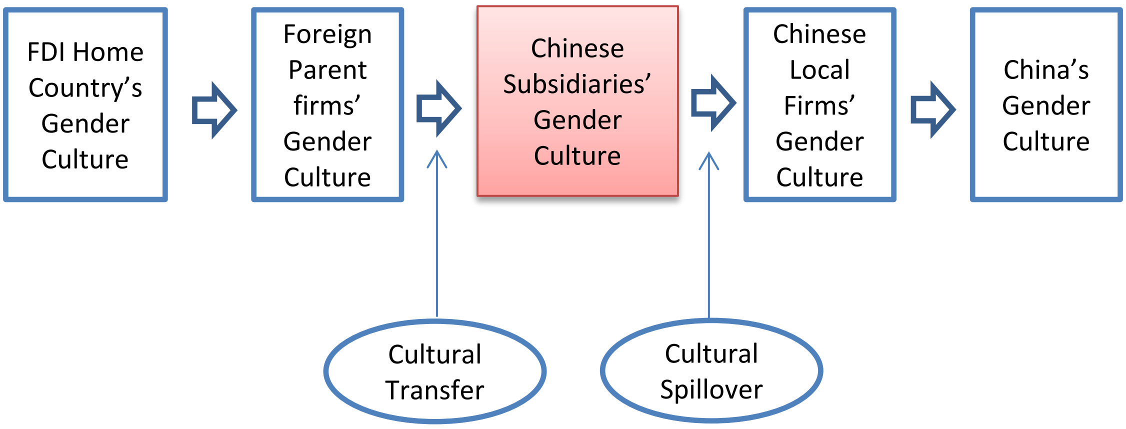

Table 1: Summary Statistics of the 2004 Data

variable	N	mean	sd
female share all workers	262,018	0.397	0.243
female share unskilled workers	240,784	0.421	0.299
female share skilled workers	255,239	0.360	0.230
female share of Chinese local firms	202,536	0.397	0.236
female share of FIEs	28,816	0.479	0.256
female share of Hong Kong, Macau and Taiwan firms	28,416	0.490	0.241
female share of FIEs from countries with GII higher than China	3,759	0.454	0.237
female share of FIEs from countries with GII lower than China	10,169	0.497	0.265
female name probability Chinese firms	208,185	0.243	0.229
female name probability FIEs	25,867	0.253	0.230
female name probability Hong Kong, Macau and Taiwan firms	26,888	0.256	0.239
female name probability of FIEs from countries with GII higher than China	2,165	0.246	0.256
female name probability of FIEs from countries with GII lower than China	6,238	0.258	0.221
Gender Inequality Index	13,921	0.174	0.098
World Value Survey score	10,583	0.554	0.147
ln(gdppc)	28,429	25.90	0.67
computer intensity	278,507	0.1472	19.3357
R&D intensity	272,948	-0.0310	20.4022
ln(TFP)	241,866	-0.9718	1.0714
skill intensity	278,507	0.0121	0.0525
capital intensity	255,449	101	1,046
output	275,460	72,743	656,030
wage rate	276,048	13.92	70.92
firm age	278,563	8.93	10.89
wholly foreign owned dummy	278,982	0.1052	0.3068
FDI presence (four-digit industry level)	278,981	0.3157	0.1956
FDI presence (city level)	278,981	0.3013	0.2341

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

Table 2: FDI Premium in Female Share of Employment and Female Probability of Legal Person Representatives (2004-2007 Panel)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Female Share of Employment						
FDI dummy	0.077	0.025	0.020			
	(25.29)***	(10.18)***	(19.18)***			
FDI from high GII countries				0.055	0.019	0.018
				(12.62)***	(5.87)***	(12.16)***
FDI from low GII countries				0.106	0.044	0.023
				(14.21)***	(7.69)***	(13.66)***
Year FE	No	Yes	Yes	No	Yes	Yes
Industry (4-digit) FE	No	Yes	No	No	Yes	No
Provincial FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
N	982,219	982,219	982,219	901,909	901,909	901,909
Panel B: Female Probability of Legal Person Representatives						
FDI dummy	0.007	0.001	0.009			
	(7.54)***	(0.88)	(5.33)***			
FDI from high GII countries				-0.002	0.001	0.005
				(0.69)	(1.22)	(1.76)*
FDI from low GII countries				0.006	0.003	0.009
				(3.76)***	(2.74)***	(3.32)***
Year FE	No	Yes	Yes	No	Yes	Yes
Industry (4-digit) FE	No	Yes	No	No	Yes	No
Provincial FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
N	805,990	805,990	805,990	744,868	744,868	744,868
Firm FE	No	No	Yes	Yes	Yes	Yes

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 3: Gender Cultural Transfer Effect - Gender Inequality Index and 2004 Regressions

	(1) female share of all workers	(2) female share of unskilled workers	(3) female share of skilled workers	(4) female share of all workers	(5) female probability of legal person representatives	(6) female share of all workers
Gender Inequality Index	-0.099 (-6.17)***	-0.113 (-4.89)***	-0.073 (-4.04)***	-0.108 (-5.22)***	-0.123 (-1.78)*	
GII*joint venture dummy				0.023 (7.85)***		
World Value Survey score						0.072 (2.09)**
ln(gdppc)	0.003 (0.95)	0.006 (1.57)	0.001 (0.37)	0.003 (0.92)	0.005 (0.82)	0.005 (1.22)
computer intensity	-0.00073 (-1.84)*	-0.049 (-4.27)***	-0.00057 (-1.27)	-0.00082 (-2.16)**	-0.032 (-4.46)***	-0.0009 (-1.73)*
R&D intensity	-0.018 (-1.81)*	0.013 (0.86)	-0.017 (-1.47)	-0.017 (-1.47)	-0.009 (-4.98)***	-0.008 (-1.30)
ln(TFP)	-0.028 (-13.25)***	-0.021 (-6.40)***	-0.027 (-8.02)***	-0.019 (-8.54)***	-0.026 (-12.47)***	-0.023 (-18.53)***
skill intensity	0.029 (0.29)	-2.156 (-7.24)***	0.248 (2.31)**	0.028 (0.31)	-0.032 (-0.65)	-0.298 (-5.54)***
ln(capital intensity)	-0.040 (-24.83)***	-0.036 (-15.40)***	-0.026 (-14.70)***	-0.026 (-14.70)***	-0.087 (-9.84)***	-0.031 (-28.34)***
ln(output)	0.020 (11.72)***	0.012 (4.37)***	0.014 (7.54)***	0.017 (9.09)***	0.014 (7.69)***	0.016 (16.33)***
ln(wage rate)	-0.023 (-8.25)***	-0.026 (-6.30)***	-0.014 (-4.48)***	-0.024 (-4.48)***	-0.084 (-8.32)***	-0.031 (-12.34)***
ln(firm age)	0.004 (2.36)**	0.003 (1.03)	0.003 (1.56)	0.003 (1.56)	0.004 (1.88)*	0.006 (8.76)***
Four-digit industry fixed	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	11,504	10,416	11,465	11,504	7,884	9,365
adj. R-sq	0.568	0.463	0.363	0.584	0.156	0.546

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 4: Female Share and Productivity - 2004-2007 Panel Regressions

Dependent Variable: ln(TFP)

	(1) All Firms	(2) All Firms
female share	-0.029	0.154
	(-8.67)***	(8.53)***
R&D intensity	0.0004	0.0006
	(0.32)	(1.25)
ln(capital intensity)	-0.304	-0.117
	(-39.67)***	(-32.31)***
ln(output)	0.195	0.773
	(37.32)***	(40.55)***
ln(wage rate)	0.096	0.023
	(26.91)***	(23.32)***
ln(firm age)	-0.0005	-0.008
	(-8.32)***	(-1.18)
Ownership fixed effects	Yes	No
Provincial fixed effects	Yes	No
Four-digit industry fixed	Yes	No
Year fixed effects	Yes	Yes
Firm fixed effects	No	Yes
N	1,033,061	1,027,491
adj. R-sq	0.901	0.705

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

Table 5: Gender Cultural Spillover Effect - 2004 Regressions

	(1) female share of all workers	(2) female share of unskilled workers	(3) female share of skilled workers	(4) female share of all workers	(5) female share of all workers	(6) female probability of legal person representatives	(7) female share of all workers
FDI in industry	0.315 (23.44)***	0.349 (14.33)***	0.223 (10.75)***		-0.203 (16.45)***	0.048 (11.90)***	
FDI in industry from high GII countries				0.156 (8.23)***			
FDI in industry from low GII countries				0.368 (21.73)***			
FDI presence * female comparative advantage					1.837 (19.65)***		
FDI in city							0.213 (21.22)***
Herfindhal Index	-0.011 (-5.43)***	-0.013 (-4.56)***	-0.008 (-5.87)***	-0.015 (-6.02)***	-0.014 (-6.63)***	0.002 (-0.76)	-0.015 (-8.98)***
computer intensity	-0.00029 (-1.28)	-0.00044 (-1.63)	-0.000013 (-0.59)	-0.00031 (-1.22)	-0.000033 (-1.54)	-0.000062 (-0.27)	0.000032 (0.54)
R&D intensity	-0.002 (-1.81)*	-0.004 (-1.91)*	-0.007 (-0.43)	-0.002 (-1.75)*	-0.002 (-1.82)*	-0.00005 (-0.01)	-0.004 (-2.21)*
ln(TFP)	-0.012 (-9.65)***	-0.006 (-7.66)***	-0.015 (-6.18)***	-0.016 (-12.89)***	-0.009 (-9.49)***	-0.002 (-3.42)***	-0.018 (-4.33)***
skill intensity	-0.823 (-17.28)***	-2.775 (-15.81)***	-0.366 (-10.42)***	-0.998 (-18.41)***	-0.664 (-14.53)***	-0.135 (-4.67)***	-0.765 (-6.67)***
ln(capital intensity)	-0.028 (-23.11)***	-0.028 (-16.63)***	-0.017 (-18.21)***	-0.026 (-24.82)***	-0.022 (-20.12)***	-0.007 (-14.32)***	-0.007 (-14.80)***
ln(output)	0.007 (9.28)***	0.003 (5.91)***	0.007 (5.53)***	0.008 (7.52)***	0.007 (10.67)***	0.004 (7.43)***	0.004 (7.22)***
ln(wage rate)	-0.038 (-14.25)***	-0.029 (-10.42)***	-0.013 (-9.59)***	-0.035 (-13.75)***	-0.025 (-12.09)***	0.001 (1.41)	-0.002 (-8.46)***
ln(firm age)	0.003 (9.83)***	0.002 (4.10)***	0.005 (4.87)***	0.005 (9.57)***	0.004 (8.58)***	0.006 (15.58)***	0.005 (16.58)***
Provincial fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	187,885	177,860	185,193	187,885	187,885	155,717	187,885
adj. R-sq	0.138	0.125	0.087	0.142	0.056	0.046	0.033

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 6: Gender Cultural Spillover Effect - 2004-2007 Panel Regressions

	(1)	(2)	(3)	(4)	(5)
	female share of all workers	female share of all workers	female share of all workers	female share of all workers	female share of all workers
FDI in industry	0.036 (9.97)***		-0.014 (-2.01)**	0.024 (4.42)***	
FDI in industry from high GII countries		0.024 (1.77)*			
FDI in industry from low GII countries		0.133 (13.21)***			
FDI presence in industry * female comparative advantage			0.174 (8.03)***		
FDI presence in industry * lagged ln(TFP)				-0.002 (-2.35)**	
FDI in city					0.062 (8.99)***
Herfindhal Index	-0.003 (-2.15)**	-0.004 (-3.22)***	-0.003 (-2.89)***	-0.004 (-3.43)***	-0.005 (-3.03)***
R&D intensity	0.000 (-0.28)	-0.0006 (-2.17)**	0.000 (-0.34)	-0.001 (-0.45)	-0.0008 (-3.13)***
ln(TFP)	0.009 (14.21)***	0.014 (13.76)***	0.011 (13.78)***	0.009 (13.95)***	0.011 (32.98)***
ln(capital intensity)	-0.016 (-18.73)***	-0.015 (-19.97)***	-0.017 (-17.73)***	-0.016 (-19.38)***	-0.017 (-39.12)***
ln(output)	0.015 (19.06)***	0.018 (16.98)***	0.016 (12.29)***	0.014 (18.62)***	0.016 (51.64)***
ln(wage rate)	-0.007 (-16.48)***	-0.006 (-15.56)***	-0.006 (-13.27)***	-0.007 (-13.44)***	-0.006 (-16.75)***
ln(firm age)	0.002 (11.08)***	0.002 (10.89)***	0.003 (9.32)***	0.002 (9.97)***	0.002 (11.81)***
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	805,990	805,990	805,990	502,095	765,457
adj. R-sq	0.571	0.581	0.592	0.554	0.445

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.

Appendix Table 1: Rankings of Chinese Characters as the Last Character in Female and Male Names

	Most frequently used characters in female names		Most frequently used characters in male names		Characters with the highest female name probability		Characters with the lowest female name probability	
Rank	Character	Percentage	Character	Percentage	Character	female probability	Character	female probability
1	兰	6.03	明	2.58	娟	0.997	彪	0.008
2	珍	5.11	林	2.42	媛	0.996	法	0.012
3	英	4.87	生	2.40	娥	0.996	刚	0.012
4	芳	3.83	平	1.78	娇	0.995	财	0.018
5	梅	3.59	军	1.63	婵	0.994	山	0.019
6	香	3.15	华	1.62	姐	0.992	豪	0.022
7	花	3.11	祥	1.43	菊	0.992	泰	0.023
8	芬	2.46	文	1.22	花	0.990	强	0.024
9	秀	2.42	成	1.14	翠	0.989	武	0.025
10	玲	2.29	国	1.13	莉	0.988	魁	0.026
Total		36.86		17.35				

Source: Authors' calculation using a random sample of the 2005 1% Population Survey.

Appendix Table 2: 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
female_prob	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 divided by total employment.
R&D/value added	R&D expenditure divided by 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.
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).