

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

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Abstract

This paper studies how foreign direct investment (FDI) contributes to cultural convergence across countries. Specifically, we examine whether multinational firms transfer corporate culture of employing women to foreign affiliates and eventually to local firms in the host country. To guide our empirical analysis, we build a parsimonious multi-sector task-based model that features heterogeneity in firms' productivity and their biases towards female workers. Workers are differentiated by gender, with women having a comparative advantage in skill-intensive versus brawn-intensive tasks, and sectors differing in their dependence on these tasks. Because discrimination lowers profits, an increased prevalence of foreign firms induce discriminating firms to increase female employment, due to both competition and imitation. Using a large manufacturing firm data set from China over the 2004-2007 period, we find that foreign-invested enterprises (FIEs) from countries with lower gender inequality tend to hire proportionately more women and are more likely to appoint female managers. In addition to the within-firm cultural transfer, we find evidence of cultural spillover from FIEs to 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 our model predictions and show that FDI lowers gender inequality through channels beyond the competition effect proposed by Becker (1957). Our results highlights an unexplored externality of FDI, in addition to technology and managerial spillovers as emphasized by existing studies.

Key Words: FDI, Culture, Gender Inequality

JEL Classification Numbers: F11, L16, O53

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1 Introduction

Gender inequality is widespread in different societies around the world.¹ Not only that it is unjust on many grounds, it results in huge economic loss (Hsieh et al., 2013). Studies have shown that empowering women promotes better social outcomes, such as improved children’s education and health (Duflo, 2012). Eliminating biases against women is hard, as prejudices against certain groups in society often have their deep historical roots. Social scientists have for years postulated that cultural differences are the ultimate causes of the variation in gender inequality across countries.² Naturally, some governments have tried to use policies to reduce prejudices against women, but the effects have been limited (Leonard, 1990).³

This paper studies how economic globalization may contribute to countries’ convergence of culture in terms of prejudice against women. Different from recent studies that emphasize how trade liberalization may induce competition and/or industrial specialization that favor women (e.g., Black and Brainerd, 2004; Juhn et al., 2013, 2014), 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 answer these questions, we use comprehensive industrial firm survey data from China, complemented with unique data on the country of origin of foreign firms. We first establish several stylized facts regarding the existence of such transfer. To the best of knowledge, such facts have not been established before. We then proceed to examine whether and how corporate culture may be spilled over from foreign affiliates to domestically owned firms, evidenced by a change in the latter’s preferences for female workers.

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 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 theoretically shows that production functions micro-founded on tasks with varying skill intensities can ultimately be expressed as a Cobb-Douglas production function with female and male labor inputs only.

Our model features heterogeneity in firms’ productivity and their degree of taste-based biases towards female workers. Firms that discriminate women more will naturally have a lower female-to-male employment ratio compared to the optimal one, all else being equal. Discrimination thus

¹See Duflo (2012) for specific examples.

²See, for instance, Inglehart and Norris (2003).

³Roland (2004) has a more general discussion on why policies has little effects on culture, an example of slow-moving institutions.

lowers profits and measured productivity. As has been postulated by many existing studies, the competitive pressure from the entry of foreign-invested enterprises (FIE), which drive up wages and/or lower goods' prices, reduce profits for all existing firms. To survive, firms that have discriminated women more, especially those that are on the verge of exit, will raise female employment by more. In addition to the competitive pressure, by illustrating a more profitable employment structure, FIEs generate cultural spillover, similar to the technology spillover in terms of mechanism. Our model shows that 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 FIEs whose home countries are less biased against women.

We study China not only because it is one of the largest recipients of FDI, but also because its biases against women have deep cultural root from Confucius philosophy that promotes the strict obligatory role of women as a cornerstone of social order and stability. In the traditional Chinese patriarchal society, males were viewed as superior. Women were supposed to follow the leadership of the males in the family, especially the father before marriage and the husband afterwards. In other words, Confucius philosophy promotes social and even physical oppression of women. After the founding of the People's Republic of China, gender inequality was significantly reduced under Mao's egalitarian philosophy.⁴ The female labor force participation rate soared, and more women became government leaders and role model workers in state-owned enterprises. However, since the economic reform implemented by the Chinese central government in the late 1970s, there has been a reversal to high gender inequality that preceded Mao's era (Cai, Zhao and Park, 2008; Gustafsson and Li, 2000). Thus, despite the recent economic success, gender inequality is still widespread in China.⁵

The main data set for the analysis is from the Annual Industrial Firm Surveys conducted by China's National Bureau of Statistics (NBS) over the period of 2004-2007. To obtain information on the country of origin of each FIE, we merge the industrial firm data with unique FDI surveys conducted by China's Ministry of Commerce. We study discrimination against women by examining female shares in a firm's total employment and by skill level. We also study the probability of a firm's appointing a female manager.⁶ To measure gender culture of different countries of origin,

⁴For 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.

⁵According 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.

⁶As we will soon explain in the data section below, we consider the legal representative as the manager of the firm. In China, a legal representative is either the chairman or CEO of the firm. We infer the gender of legal person representatives based on their names.

we use country-level indices of gender inequality from the United Nations Development Program (UNDP), a de facto measure, as well as the average perception towards women from the World Value Survey (WVS).

We find evidence supporting our model predictions regarding both cultural transfer and cultural spillover. We show that in China, FIEs employ more women and are also more likely to appoint women as managers, compared to local firms. Our regression results reveal that the gap in female employment between local firms and FIEs is decreasing in measured gender inequality of the investing countries. These patterns hold within narrowly defined industries (over 480) and provinces, and remain robust to the control of a wide range of firm characteristics, in particular technology. We find that cultural transfer is more pronounced within wholly-owned FIE, compared to joint ventures. To the extent that larger equity ownership implies more control by the multinational headquarters, the findings of a stronger spillover effect among wholly-owned FIE are consistent with our hypothesis that culture is transferred from the top, instead of in the opposite direction as would be observed if FIE adapt to local culture. As predicted by our model, we find that firms become more productive after increasing their female employment shares.

We also find evidence of cultural spillover from FIE to local firms, evidenced by changes in firms' female employment. Using the empirical strategy prevailing in the FDI spillover literature (Aitken and Harrison, 1997; Javorcik, 2004), we find that the prevalence of FDI in the same sector or city is positively correlated with the share of women in the firm's employment, as well as the probability of the firm's appointing a female manager. The cultural spillover effect is stronger in sectors in which females have a comparative advantage, among the less productive firms, and from countries with lower gender inequality. These differential spillover effects across countries of origin implies that the FDI spillover effect on female employment is above and beyond the traditional forces due to increased competition, as proposed by Becker (1957).

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 - 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. Recent research in economics studies the cost of discrimination (Mortvik and Spant, 2005; Cavalcanti and Tavares, 2007; Hsieh et al., 2013). In particular, 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 between gender and racial groups. Complementing the findings of Hsieh et al. (2013), we provide the first piece of micro 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.

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.⁷ Most of these sociology and anthropology studies are either pure theories or case studies. Our paper provides rigorous empirical evidence using a large-scale firm-level data set. Our findings lend support to the cultural convergence hypothesis. It also complements recent studies in economics, which examine specific channels through which cultural values can be transferred 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 firms that discriminate less. 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 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 (e.g., Aitken and Harrison, 1997, Javorcik, 2004, among others). Economic research has cumulated a rich stock of knowledge about how economic globalization can facilitate cross-border transfer of knowledge, technology, and managerial know-how. However, there is relatively scant evidence on the transfer of culture.

Finally, our project is naturally related to the growing 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 discrimination, we provides evidence that FDI can be used as a vehicle to change social norms.

⁷They 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".

The rest of the paper proceeds 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 model predictions about the transfer and spillover of cultural values regarding employment of women. 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 in the main text 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, face their own demand, and charge their own prices. The model features heterogeneous firms, monopolistic competitive goods markets, and constant-elasticity-of-substitution preferences, as in Melitz (2003). Firms are heterogeneous along two dimensions – productivity and the degree of discrimination. 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. 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 and discrimination factor γ has revenue equal to $R(\varphi, \gamma) = A_j^{1-\eta} y(\varphi, \gamma)^\eta$, 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 its preference for discrimination. The aggregate consumption bundle is set as the numeraire.

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 inputs of all tasks, which is represented by 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 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 labor inputs of skills (S) and brawn (B) 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 index i indicates a more intensive use 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 has its micro-foundation at the underlying task level.

Similar to AA, we show in the appendix that without any labor market frictions, wages for skill and brawn inputs are the same regardless of which sectors or tasks the inputs are being employed. As such, in equilibrium, high- i tasks use only skills as inputs while low- i tasks only brawn.

2.1.3 Labor Supply

Labor is differentiated in terms of gender and skills. The economy is endowed with M male workers and F female workers. 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 male workers, female workers are endowed with more skills than brawn (e.g. Pitt et al., 2012, Alesina et al., 2013).⁸ 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 to supply brawn or skills. In the appendix, we show 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 completely specialize in what they are relatively better at. Therefore, there is a one-to-one mapping between skill and female labor supply, as well as a one-to-one mapping between brawn services and male labor supply. In other words, within each sector, high- i tasks are always supplied

⁸If 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.

by women while low- i tasks are always supplied by men.⁹ In the appendix, we show that the firm's maximization problem becomes one that maximizes a Cobb-Douglas production function over male and female labor, subject to a prejudice disutility from hiring women.

2.1.4 Firm Equilibrium

We now analyze how heterogeneities in firms' discrimination and sectors' female comparative advantage affect a firm's equilibrium employment and profits. We suppress sector subscripts to simplify notation. Following Becker (1957) and the subsequent studies, we consider taste-based discrimination and abstract away from statistical discrimination.¹⁰ To this end, we use γ to represent the amount of utility loss for the firm's owner in terms of revenue units. For each additional unit of female labor hired, the disutility for the firm owner is equivalent to losing γ units of revenue.

Consider a firm with productivity level, φ , and a discrimination parameter, γ . The firm's objective is to maximize operating profits net the utility loss of discrimination (i.e., $\pi^o(\varphi, \gamma) - \gamma f$) by choosing male (m) and female (f) employment, taking wages as given. With monopolistic competition along with CES utility, the firm's optimization problem takes the following form:

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

where μ is a sector-specific parameter (see the appendix), w_f is the female wage rate, w_m is the male wage rate, γ is the discrimination parameter, and ϕ is the fixed cost of production, measured in the terms of the bundle of inputs with the same proportion of female and male labor as the variable cost.

Solving the firms' maximization problem 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

⁹Obviously 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.

¹⁰In the empirical analysis below, we will provide evidence to show the relative contribution of taste-based relative to statistical discrimination.

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:

$$\Delta \left(\frac{f}{m} \right) = -\frac{\beta}{1 - \beta} \frac{\gamma}{w_f + \gamma}, \quad (1)$$

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 $\gamma = 0$). The magnitude of the deviation from the theoretically optimal employment ratio is increasing in the firm's degree of discrimination (γ), decreasing in w_f , and increasing in β .

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, what we need to have is data on multinational affiliates from different countries of origin and study their differences, with a counterfactual optimal of female-male employment ratio in mind. With such a data set from China, we empirically examine the following prediction implied by (1).

Prediction 1 (Female employment)

Firms from countries that discriminate women more have a smaller female-to-male ratio within an industry. The negative relationship is smaller if female wages are higher (e.g., more skill-intensive), and larger in sectors in which female workers have a comparative advantage (higher β).

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

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

where $\Lambda = (1 - \eta) A \left(\mu \beta^\beta (1 - \beta)^{1-\beta} \right)^{\frac{\eta}{1-\eta}}$ 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 (Profits and productivity)

All else being equal, firms that discriminate women more have smaller measured profits. Given sufficiently large fixed costs, their measured TFP are also smaller.

Two firms with the same 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 treats 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 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 from 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 suggests a positive 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 also 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 not only on the firm's own discrimination parameter, but also foreign firms' in the same sector (city). The implicit assumption is that firms imitate the employment practices of their foreign competitors, which are more profitable and productive due to a lower degree of discrimination, all else being equal. Notice that this is above and beyond the standard competition effect, as proposed by Becker (1958). Even in the absence of competition, for the sake of maximizing profits, firms would always have incentives to do that if they are shown the more profitable way of business. Of course, the competition effect shall induce imitation. Based on imitation, the discrimination parameter of the firm will depend on the number of foreign firms in

the same sector (city) and their discrimination parameters. We express such an idea in a reduced form as follows:

$$\gamma(n, \tilde{\gamma}) = \gamma^{1-\delta(n)} \tilde{\gamma}^{\delta(n)}. \quad (3)$$

where $\tilde{\gamma}$ is the average discrimination factor of foreign firms in the same sector (city). $\delta(n)$ 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 $\delta'(n) > 0$.¹¹ Since

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

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 $\tilde{\gamma}$. Simple comparative static shows that

$$\frac{\partial \ln \gamma(n, \tilde{\gamma})}{\partial n \partial \tilde{\gamma}} = \frac{\delta'(n)}{\tilde{\gamma}} > 0, \quad (5)$$

and thus, domestic firms respond by increasing female employment if more foreign firms in the same sector are from countries with less discrimination. 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:

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

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.

Prediction 4 (Cultural spillover)

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

¹¹A standard statistical learning model, based on either Bayesian updating or Degroot's learning (Degroot, 2004), can serve as a micro-foundation of this equation.

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. The data set 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 data set 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 on firm employment breakdown by gender and education.¹²
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 2004.¹³

Notice that our data do not provide a wage breakdown by gender. With this limitation, we can only study gender inequality in employment across firms, but not in wages. In the empirical analysis, we use information on firms’ registration types to identify foreign invested enterprises (FIE). To measure firm performance, we estimate firm TFP using the Olley-Pakes procedure.

3.2 Ministry of Commerce FDI Survey Database

The NBS firm-level data set does not provide information on the country of origin of a firm’s foreign investors. To overcome this problem, we obtain such information at the firm level from China’s

¹²2004 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.

¹³An 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.

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 the following two data sets:

3.3.1 UNDP Gender Inequality Index

The most commonly used data in the cross-country gender studies is the United States Development Program (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 market participation. A higher GII value indicates greater gender inequality. We use the 2012 Gender Inequality Index, which covers 149 countries. 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, 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). In our regression analysis, we will control for countries' income level and other characteristics.

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 perception 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, Panel B of Table 1 shows that countries with the highest WVS scores are Egypt, Jordan, Mali, India and Iran. Countries with the five lowest WVS score are Sweden, Norway, France, Finland and Canada. The ranking of WVS indices is highly correlated with that of GII.

Unfortunately, GII and WVS 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 the same if we had the data anyway.

3.4 Managers (Legal 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 prevents women from taking high-level management positions (Nevill et al., 1990). Does gender cultural transfer also affect firms’ appointment 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 representatives in our data. In China, legal representatives are typically the CEOs, presidents, or general managers of the firms. We only have names of the managers but no information on the gender of these legal 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.¹⁴ 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 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 Table A1 in the appendix list ten most frequently used Chinese characters that appear as the last characters of the female and male names, respectively.

¹⁴Most 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.

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:

$$female_prob_i = \frac{frequency_female_i}{frequency_female_i + frequency_male_i}, \quad (6)$$

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 Table A1 in the appendix report the Chinese characters with the highest $female_prob$ and lowest $female_prob$. For the top 10 most common frequent characters used in female names, the probability that the character is used by a man is always smaller than 1% based on the sample with over 2.5 million names.

3.5 Summary Statistics

Table 2 reports summary statistics of 2004 variables 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 also have higher probability to hire women as legal representatives. 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 2 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) than those of local firms. There are several possible explanations: First, that may be a result of selection. Those FIEs from high GII countries may not be the typical firms in their home countries. If FDI is associated with a significant sunk cost, only the most productive firms would find it profitable to conduct FDI in China (e.g., Helpman, et al., 2004). Since our model shows a positive correlation between productivity and female employment share, the higher female employment ratio among FIEs could be driven by the firms' self-selection into FDI based on productivity. In the regression analysis on cultural transfer, we will control for a host of firm characteristics, including TFP. It is worth noting that if we find stronger cultural transfer effects from investing countries that have a lower gender inequality, the productivity sorting effect by itself is insufficient to explain the pattern. Moreover, the potential selection bias is absent in the cultural spillover regressions, where only local firms are included in the sample of analysis. We will discuss the relevance of potential selection bias when we present the empirical findings. Second, the FIEs from high gender inequality countries may change their employment practices in the Chinese market in order to compete with other FIEs from low gender inequality countries. 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 violate Chinese labor laws.

From Table 2's 2004 data summary statistics, we see that FIEs have a significantly higher female share in employment and a higher probability to appoint a woman as the manager (legal representative). To examine this pattern more systematically, in Table 3 we use firm panel data over the 2004-2007 period and regress the share of female workers of the firm (Panel A) or the probability of the firm's appointing a female manager (Panel B) on the firm's FDI dummy. The dummy will be equal to 0 for the Chinese domestically owned (local) firms. Column (1) in Panel A shows that the FIEs' female share of employment is on average 7.7 percentage points higher than the Chinese firms. When industry and province fixed effects are controlled for, the coefficient drops to about 2.5 percent (column (2)). This could be driven by the fact that FIEs self-select into industries in which women have a comparative advantage, or to provinces where the supply of female labor is higher. To this end, we add an interaction term between the firm's FDI dummy and a sectoral measure of female comparative advantage in column (3). The measures of female comparative advantage at the sector level come from Do, Levchenko and Raddatz (2014), who compute the female share in employment in each industry using the data from a wide range of countries. The measures are available at the ISIC level. We create a concordance table between ISIC and Chinese industry classification. Appendix Table A2 lists the sectors with the highest and lowest female comparative advantage. 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. The positive sign on the interaction term in column (3) implies that the female share gap between the FIEs and Chinese local firms is wider in sectors that traditionally hire more women. This finding lends indirect support to Prediction 1 of our model. Column (4) in Table 3 includes firm fixed effect to control for all unobserved firm characteristics that may affect the female employment ratio. Identification comes only from the firms that switched between foreign ownership and domestic ownership. The coefficient indicates that a switch from domestic to foreign ownership is associated with a 2 percentage-point increase in the firm's female share. Panel B reports the results of the same regressions, using *female_prob* as the dependent variables instead. The FDI dummy is statistically significant in columns (1) and (4).

4 Estimating the FDI Gender Cultural Transfer to Chinese Subsidiaries

Figure 1 summarizes the procedures of our empirical exploration. We first examine the existence of cultural transfer within firms - that multinational firms carry their home countries' gender culture to their Chinese affiliates, which in turn affect their female employment shares.

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

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

where S_{ij} is foreign firm i 's share of female workers or a dummy equal to 1 if it has a female manager (legal representative). Index j represents the country of origin. GII_j is a measure of gender inequality in country j , while $income_j$ 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 A3 for the definitions and the data sources of all these variables. $\{FE\}$ represent fixed effects, which include four-digit industry fixed effects and province fixed effects. ε_{ij} is the error term.

The challenge in the empirical analysis is to control for all confounding factors. In equation (7). we include home country GDP per capita to control for a wide range of potential factors from the investing countries that are related to the stage of development. We also include several firm characteristics and industry fixed effects to control for 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 can be major determinants of female employment. We include a full set of province fixed effects to control for time-invariant unobservable heterogeneity across regions. As we are examining the different effects from countries with different gender culture, the sample includes all FIEs and excludes all local firms.

Table 4 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 4. Computer intensity, R&D intensity, TFP and

wage rate are all negatively correlated with firms' female employment ratio. An obvious potential difference between local firms and FIEs is their technologies, but our results show that technology do not appear to be the main drivers of female employment shares among FIEs. The significantly negative relation between firms' female share and technology, proxied by higher computer and R&D intensity, reveals that FIEs adopting advanced technology tend to have a smaller female employment share.

In the first few years after foreign firms invested in China, FIEs may bring the culture from their home country to China. However, such foreign culture may dissipate over time if FIEs assimilate themselves with the local culture and behave more like a local firm. If cultural assimilation is pervasive, we would expect to see a negative relationship between firms' female employment share and age. Results reported in Table 4 lend no support to this hypothesis. The coefficient on firm age is positive and statistically significant in columns (1) and (5), and positive but insignificant in other columns. Older FIEs do not appear to hire fewer women.

In columns (2) and (3), we change the dependent variable to investigate potential differential cultural transfer effects between skilled and unskilled workers. We find that GII has a negative sign in both columns (2) and (3), but it is larger in column (2), indicating that the gender cultural transfer effect is stronger among the unskilled employment across firms. To the extent that skilled workers have higher wages, this finding supports the second part of Prediction 1, which proposes that discrimination should have a smaller employment effect for high-wage female workers. We also find that higher skill intensity is associated with a higher female employment share of the firm, while it is negatively correlated with the share of unskilled female workers. This may explain why skill intensity is not statistically significant when skilled and unskilled labor is combined in column (1).

How much an FIE transfer the foreign culture depends not only on its home country's culture, but also how much control it has over its affiliates' decisions. One therefore expects a stronger cultural transfer within wholly-owned FIEs than joint ventures. In column (4), we add an interaction term between GII and the joint venture dummy. The coefficients of the interaction term is positive and significant, suggesting that cultural transfer is weaker among joint ventures.

Column (5) uses the dummy of whether the FIE hires female manager as the dependent variable. We find a negative and significant correlation between GII and the probability, suggesting 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 management level 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 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 $\ln(\text{TFP})$ on female share and other control variables using the 2004-2007 data. As is shown in Table 5, column (1) shows a negative and significant coefficient on the firm’s female share. While it seems to contradict Prediction 2, the coefficient turns positive and significant when we control for firm fixed effects. To the extent that controlling for firm fixed effects eliminates the biases introduced by omitted firm heterogeneity, our results support Prediction 2 that less prejudice against women by the firm contributes to firm productivity.¹⁵

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 appointing a female manager as the measures of the firm’s prejudices against women. We adopt the empirical specification widely used in the literature on FDI technology spillover (e.g., Aitken and Harrison, 1997; Javorcik, 2004) as follows:

$$S_{ik} = \beta_0 + \beta_1 FDI_presence_k + \mathbf{X}'_{ik}\gamma + \{FE\} + \varepsilon_{ik}, \quad (8)$$

where S_{ik} is firm i ’s share of female workers or an its indicator for having a female manager. Index k represents an industry. $FDI_presence_k$ is FIE’s share of total output in industry k . \mathbf{X}_{ik} is 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 battery of fixed effects. Importantly, we also include a Herfindahl index of the industry to control for the changes in the competitiveness of the industry. As pointed in the literature, competition will drive firms to discriminate less, or else they will be driven out from the market.

Our theoretical model shows that FIEs can affect local firms’ female employment share due to competition and imitation. As often emphasized by the FDI literature, local firms learn from FIEs in the same industry or region about product designs and/ or production technology. They may also learn from FIEs about more profitable corporate culture. Moreover, technology imitation or spillover can also be gender-biased. One well-known example, as the literature has shown, is

¹⁵Note 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.

about how a more intensive use of computers and information technology increases the demand for female labor significantly. 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 value or preference of Chinese local firms. To identify cultural spillover, we include the Herfindahl index of the industry and the firm's R&D expenses to control for the potential competition effect and gender biased technology spillover effect.

We estimate equation (8) using a sample of Chinese local firms (excluding all FIEs since we are studying FDI spillover). As shown in the first two columns of Table 6, foreign presence is positively correlated with the share of female employment, regardless of whether we use the 2004 cross-sectional sample or the 2004-2007 panel sample, which allows for the control of firm fixed effects. These results lend support to Prediction 4. Comparing the results between columns (3) and (4), the spillover effect is stronger for the ratio of female unskilled workers, whom Chinese firms are presumably more biased against. Column (5) uses the firm's dummy for appointing a female manager as the dependent variable. The prevalence of FIEs in the sector is positively correlated with the probability that a local firm will hire a female manager. The effect is statistically significant at the 1% level.

Since physical distance may matter for cultural spillover, the last column of Table 6 uses an alternative measure of FDI presence - the FDI output share in the same city, instead of the same industry. The last two columns of Table 6 show positive and significant cultural spillover from FIEs to local firms in the same city. The results remain robust when we use the 2004-2007 sample and control for firm fixed effects.

Table 7 examines whether the spillover effect differs across industries, countries of origin, and firms with heterogeneous productivity. In column (1), we include an interaction term between FDI presence and the average GII, which is calculated as the weighted average GII of the FDI country of origins. The results are consistent with our earlier findings. We find weaker spillover from FIEs coming from a high gender-inequality country. In column (2), we add an interaction term between FDI presence and industry-level female comparative advantage. Column (3) and (4) repeat the exercise in columns (1) and (2), respectively, but use the panel data set over the 2004-2007 period for analysis. The results remain robust and confirm the results based on the 2004 cross-sectional sample. 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 or the stronger the female comparative advantage in the sector is.

In column (5), we include an interaction term between the prevalence of FDI in the industry

and the local firm's lagged log TFP. We aim to test Prediction 3 that ex-ante less productive firms choose to reduce discrimination more when facing FDI inflow. 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 prediction.

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 appoint 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 spillover that have been documented in the literature, FDI may be an important vehicle to transfer 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:

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

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 products 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 $H(\gamma)$, which is assumed to be independent of $G(\varphi)$. 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 $k \in [0, 1]$ 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 $i \in [0, 1]$ 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 $y(i_j^*)$ can be done at the same cost by using skills only, which costs $\frac{w_B}{\alpha_B(i_j^*)}$, or brawn only, which costs $\frac{w_S}{\alpha_S(i_j^*)}$. 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 $i > i_j^*$ 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

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

where $p_j(i)$ is the price of task i used in sector j . In other words, given constant w_B , w_S , $\alpha_B(i)$, and $\alpha_S(i)$, $p_j(i)$ 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

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

where TVC stands for total variable cost.

Thus, for any two tasks that use brawn services

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

Given constant w_B and w_S across tasks, we have

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

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

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

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

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

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

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).¹⁶ 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

$$\frac{\theta_m^S}{\theta_m^B} > \frac{\theta_f^S}{\theta_f^B}. \quad (10)$$

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:

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

¹⁶If 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.

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 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 $B = \theta_f^B M$.

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 and discrimination parameter γ .

Under monopolistic competition with CES utility as specified above, the firm maximization problem is

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

where π^o stands for operating profits (profit excluding fixed cost), 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:

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

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 difference between workers beside gender, all female workers supply skills and get the same wage rate. Specifically,

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

where i^* is defined in Proposition 1.

Similarly, the wage rate for male workers is

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

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

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

where $\mu = \prod_{i=0}^{i^*} \left(\frac{\alpha_B(i)}{\theta_m^B} \right)^{\beta(i)} \prod_{i=i^*}^1 \left(\frac{\alpha_S(i)}{\theta_f^S} \right)^{\beta(i)}$, $\beta = \int_{i^*}^1 \beta(i) di$, $w_m = w_B \theta_m^B$, $w_f = w_S \theta_f^S$, and ϕ is the fixed cost measured in terms of the input bundle with the same factor shares as the variable cost.¹⁷

¹⁷The choice of the denomination of fixed costs is to preserve female comparative advantage, regardless of the level of the fixed costs.

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 less female workers.

$$m^* = A (\eta \mu^\eta)^{\frac{1}{1-\eta}} \varphi^{\frac{\eta}{1-\eta}} \left[\beta^\beta (1 - \beta)^{1-\beta\eta} (w_f + \gamma)^{-\beta\eta} w_m^{\beta\eta-1} \right]^{\frac{1}{1-\eta}}$$

$$f^* = A (\eta \mu^\eta)^{\frac{1}{1-\eta}} \varphi^{\frac{\eta}{1-\eta}} \left[\beta^{1-\eta(1-\beta)} (1 - \beta)^{(1-\beta)\eta} (w_f + \gamma)^{(1-\beta)\eta-1} w_m^{-(1-\beta)\eta} \right]^{\frac{1}{1-\eta}}$$

Measured labor productivity is $\tilde{\varphi}(\varphi) = \frac{pq}{x}$, where x is the input bundle, i.e. $f^\beta m^{1-\beta}$. Using the identity that total employment can be decomposed into workers who are hired for the fixed cost (ϕ) and those who are hired for actual production, measured productivity can be written as

$$\begin{aligned} \tilde{\varphi}(\varphi) &= \frac{p\varphi(x - \phi)}{x} \\ &= (w_f + \gamma)^\beta w_m^{1-\beta} \left(\frac{\sigma}{\sigma - 1} \right) \left(1 - \frac{\phi}{x} \right). \end{aligned}$$

Since $x = \left[A^{1-\eta} \eta \mu^\eta \varphi^\eta \left(\frac{w_m}{1-\beta} \right)^{-(1-\beta)} \left(\frac{w_f + \gamma}{\beta} \right)^{-\beta} \right]^{\frac{1}{1-\eta}} + \phi$ is clearly decreasing in γ , $\tilde{\varphi}(\varphi)$ is decreasing in γ if

$$\frac{d \ln \tilde{\varphi}(\varphi)}{d\gamma} = \frac{\beta}{w_f + \gamma} \left[1 - \frac{1}{1 - \eta} \frac{\phi}{x_v} \right] < 0.$$

where $x_v = x - \phi$. The condition will hold as long as $\frac{\phi}{x_v + \phi} > \frac{1-\eta}{2-\eta}$. In other words, the inequality is more likely to hold if fixed cost is sufficiently large.

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:

$$\begin{aligned} \Delta \left(\frac{f}{m} \right) &= - \left(\frac{f}{m} \right)^{nd} \frac{\gamma}{w_f + \gamma} \\ &= - \frac{\beta}{1 - \beta} \frac{\gamma}{w_f + \gamma} \end{aligned}$$

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

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., more skill-intensive), and higher in sectors in which female workers have a comparative advantage (higher β).

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 $\Lambda = (1 - \eta) A \left(\mu \beta^\beta (1 - \beta)^{1-\beta} \right)^{\frac{\eta}{1-\eta}}$ 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

All else being equal, firms that discriminate women more have smaller measured profits. Given sufficiently large fixed costs, their measured TFP are also smaller.

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 choose to reduce discrimination by more, in response to increased FDI flows in the same sector or city.

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:

$$\gamma(n, \tilde{\gamma}) = \gamma^{1-\delta(n)} \tilde{\gamma}^{\delta(n)}. \quad (11)$$

where $\tilde{\gamma}$ is the average discrimination parameter of foreign firms in the locality (sector or province). $\delta(n)$ 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 $\delta'(n) > 0$, 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 $\gamma(n, \tilde{\gamma})$. Notice that complementing the competition effect due to increasing wages, we have

$$\begin{aligned} \frac{\partial \ln \gamma(n, \tilde{\gamma})}{\partial n} &= \delta'(n) \ln \left(\frac{\tilde{\gamma}}{\gamma} \right) > 0 \text{ if } \tilde{\gamma} > \gamma \\ \frac{\partial \ln \gamma(n, \tilde{\gamma})}{\partial n \partial \tilde{\gamma}} &= \frac{\delta'(n)}{\tilde{\gamma}} > 0. \end{aligned}$$

Proposition 5

Domestic firms' female employment ratios are 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 is, or the stronger the female comparative advantage in the sector is, given the same level of FDI.

Figure 1: An Empirical Framework of Gender Cultural Diffusion

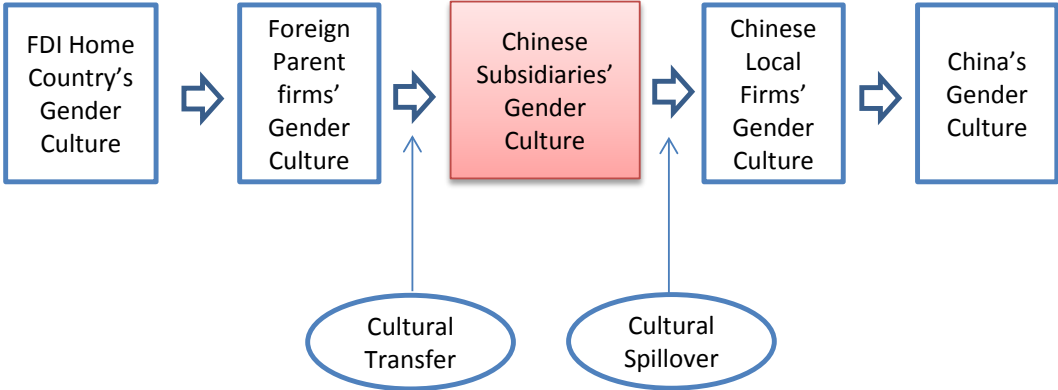


Table 1: Countries with Lowest and Highest UNDP Gender Inequality Index and World Value Survey Score

	Country	Gender Inequality Index		Country	Gender Inequality Index
Panel A: UNDP Gender Inequality Index					
1	Sweden	0.065	1	Iraq	0.799
2	Denmark	0.068	2	Yemen	0.782
3	Netherlands	0.077	3	Afghanistan	0.746
4	Norway	0.083	4	Niger	0.729
5	Switzerland	0.084	5	Mali	0.707
Panel B: World Value Survey Score					
1	Sweden	0.876	1	Egypt	0.373
2	Norway	0.875	2	Jordan	0.423
3	France	0.815	3	Mali	0.438
4	Finland	0.797	4	India	0.446
5	Canada	0.792	5	Iran	0.497

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

Table 2: Summary Statistics of the 2004 Data

variable	N	mean	sd
Country Level			
Gender inequality index	137	0.419	0.195
World Value Survey score	58	0.649	0.124
ln(GDP per capita)	197	8.060	1.671
Industry Level (Four Digit)			
Female comparative advantage	482	0.268	0.105
FDI presence (4-digit industry)	482	0.344	0.218
City Level (Four Digit Geographic Code)			
FDI presence (city)	345	0.155	0.182
Firm Level			
Female share all workers	258,899	0.411	0.243
Female share unskilled workers	240,787	0.437	0.299
Female share skilled workers	255,239	0.370	0.230
Female share of Chinese local firms	202,536	0.390	0.236
Female share of FIEs	28,450	0.482	0.256
Female share of Hong Kong, Macau and Taiwan firms	28,031	0.494	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 all firms	217,181	0.246	0.277
Female name probability Chinese firms	170,501	0.243	0.277
Female name probability FIEs	23,243	0.255	0.273
Female name probability Hong Kong, Macau and Taiwan firms	23,436	0.252	0.282
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
Joint-venture dummy	278,982	0.110	0.227

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

Table 3: FDI Premium in Female Share of Employment and Female Probability of Legal Person Representatives (2004-2007 Panel)

	(1)	(2)	(3)	(4)
Panel A: Female Share of Employment				
FDI dummy	0.077 (25.29)***	0.025 (10.18)***	0.002 (2.29)**	0.020 (19.18)***
FDI x female comp adv.			0.072 (6.22)***	
Year FE	No	Yes	Yes	Yes
Industry (4-digit) FE	No	Yes	Yes	No
Provincial FE	No	Yes	Yes	No
Firm FE	No	No	No	Yes
N	982,219	982,219	982,219	982,219
Panel B: Probability of having a female manager				
FDI dummy	0.007 (7.54)***	0.001 (0.88)	0.001 (0.45)	0.009 (5.33)***
FDI x female comp adv.			0.012 (1.45)	
Year FE	No	Yes	Yes	Yes
Industry (4-digit) FE	No	Yes	Yes	No
Provincial FE	No	Yes	Yes	No
Firm FE	No	No	No	Yes
N	805,990	805,990	805,990	805,990
Firm FE	No	No	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 4: Gender Cultural Transfer Effect - 2004 Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	female shr in total emp	female shr in unskilled emp	female share in skilled emp	female share in total emp	probability of female manager	female shr in total emp
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 5: Female Share and Productivity - 2004-2007
Panel Regressions**

Dependent Variable: ln(TFP)		
female share	-0.030 (-8.87)***	0.155 (8.68)***
R&D intensity	0.0004 (0.32)	0.0006 (1.25)
ln(capital intensity)	-0.311 (-38.66)***	-0.115 (-33.61)***
ln(wage rate)	0.089 (26.96)***	0.022 (23.67)***
ln(firm age)	-0.0005 (-8.13)***	-0.008 (-1.17)
Ownership fixed effects	Yes	No
Provincial fixed effects	Yes	No
Industry fixed effects (4 digit)	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 6: Gender Cultural Spillover Effect

Sample:	(1) 2004	(2) 2004-2007	(3)	(4) 2004	(5)	(6)	(7) 2004-2007
Dependent Variable:	female share in total emp	female share in total emp	female share in unskilled emp	female share of skilled emp	probability of female manager	female share in total emp	female share in total emp
FDI in industry	0.315 (23.44)***	0.036 (9.97)***	0.349 (14.33)***	0.223 (10.75)***	0.048 (11.90)***		
FDI in city						0.213 (21.22)***	0.062 (8.99)***
Herfindhal Index	-0.011 (-5.43)***	-0.003 (-2.15)**	-0.013 (-4.56)***	-0.008 (-5.87)***	0.002 (-0.76)	-0.015 (-8.98)***	-0.005 (-3.03)***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	No	Yes	Yes	Yes	No	No
Year fixed effects	No	Yes	No	No	No	No	Yes
Firm fixed effects	No	Yes	No	No	No	No	Yes
N	187,885	805,990	177,860	185,193	155,717	187,885	765,457
adj. R-sq	0.138	0.571	0.125	0.087	0.046	0.033	0.445

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 7: Gender Cultural Spillover (Differential Effects)

	(1)	(2)	(3)	(4)	(5)
Sample:	2004		2004-2007		
Dependent Variable:	female share in total emp				
FDI in industry	0.412 (22.98)***	-0.203 (16.45)***	0.041 (9.17)***	-0.014 (-2.01)**	0.024 (4.42)***
FDI in industry* average GII	-0.264 (5.84)***		-0.182 (4.23)***		
FDI presence * female comparative advantage		1.837 (19.65)***		0.174 (8.03)***	
FDI presence in industry * lagged ln(TFP)					-0.002 (-2.35)**
Herfindhal Index	-0.009 (-5.73)***	-0.014 (-6.63)***	-0.005 (-3.82)***	-0.003 (-2.89)***	-0.004 (-3.43)***
Controls	Yes	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	No	No	No
Year fixed effects	No	No	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes	Yes
N	187,885	187,885	805,990	805,990	502,095
adj. R-sq	0.141	0.056	0.580	0.592	0.554

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.

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

Rank	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	
	Character	%	Character	%	Character	female prob.	Character	female prob.
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: Top and Bottom 10 Sectors in terms of World Female Comparative Advantage

Top 10	Sectors	Female Share in Employment	Bottom 10	Sectors	Female Share in Employment
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. Source: Do, Levchenko, and Raddatz (2014).

Appendix Table 3: 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 least 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_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 perpetual 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).