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

Heiwai Tang†

University of Hong Kong and Johns Hopkins University

Yifan Zhang‡

Chinese University of Hong Kong

February 7, 2021

Abstract

We study the global diffusion of culture through multinationals, focusing on gender norms. Using data on manufacturing firms in China over 2004-2007, we find that foreign affiliates from countries with a more gender-equal culture tend to employ proportionally more women and appoint female managers. They also generate cultural spillovers, increasing domestic firms' female labor shares in the same industry or city. Based on a multi-sector model with firm heterogeneity in productivity, gender biases, and learning, we perform counterfactual exercises. Hypothetically eliminating firms' gender biases raises China's aggregate total factor productivity by 5%, of which spillovers from multinationals account for 19%.

Key Words: cultural spillovers, gender inequality, FDI, misallocation, China

JEL Classification Numbers: F11, F21, J16, L22, O47

*We thank seminar and conference participants at Bank of Finland's Inst for Econ in Transition, Boston U, Cornell, CUHK, HKUST, ILO, Indiana, Inter-American Development Bank, Johns Hopkins SAIS, Keio, Kobe, Shanghai Jiaotong, RIETI, Syracuse, Tsinghua, Virginia, Waseda for their helpful comments and discussions. We thank Andrei Levchenko for sharing data; Ann Harrison, Chang-Tai Hsieh, and Michael Song for comments; and Liuchuan Deng and Yui Law for excellent research assistance. The usual disclaimer applies.

†Corresponding author. Business School, University of Hong Kong, Pokfulam Road, Hong Kong. Email: tangecon@hku.hk.

‡Department of Economics, Chinese University of Hong Kong, Shatin, New Territories, Hong Kong. Email: yifan.zhang@cuhk.edu.hk.

1 Introduction

Multinational firms have been an important vehicle for cross-country diffusion of ideas, capital, and technology.[1] Besides advancing global economic convergence, social scientists have long studied how multinationals can shape host countries' social norms and values, which contribute to possible global cultural convergence.[2] That said, economics research on the cultural effects of foreign direct investment (FDI) has been scant, in part because of the challenges in quantifying culture, let alone identifying its diffusion.

This paper contributes to the debate on the cultural effects of economic globalization by studying how multinational firms transmit gender norms from their countries of origin to host countries. We use microdata on manufacturing firms in China to examine cultural transfers within multinational firm boundaries and cultural spillovers to domestic firms. Studying China's gender inequality is interesting for several reasons.[3] The first reason is due to the country's deep cultural links to Confucianism, which advocates a strict obligatory role of women. The second reason is because of the rapid rise in income and gender inequality in China after its government's embarkment of market reforms since the late 1970s (Cai, Zhao and Park, 2008).[4]

We show that policies aiming to attract foreign direct investment may have an unexpected productivity effect due to multinational firms' diffusion of culture. By inferring Chinese firms' attitudes towards women from their female labor shares within detailed industries, we find in the Chinese manufacturing firm sample that foreign affiliates from countries with a more gender-equal culture tend to employ proportionally more women and appoint female managers. In particular, we find that a one standard-deviation decrease in the country of origin's gender inequality (equivalent to reducing Malaysia's gender inequality to that of

[1] See the literature reviews by Harrison and Rodriguez-Clare (2010) and Alfaro (2017).

[2] Writings on cultural homogenization and clashes are widespread, ranging from Thomas Friedman's (1999) famous work that claims "No two countries with McDonald's have ever gone to war since each got its McDonald's," to the classic book "The Clash of Civilizations and the Remaking of World Order" by Samuel Huntington (1996). See the literature review for details.

[3] Gender prejudice has been shown to have a significant impact on China's macroeconomic outcomes, such as saving rates (Wei and Zhang, 2011). Instead of studying the consequences of discrimination, we provide evidence that FDI can be used as a vehicle to change social norms.

[4] According to a survey of more than 3,000 women conducted in 2009 by the Center for Women's Law and Legal Services at Peking University, more than 20 percent say employers cut salaries for women who become pregnant or give birth and 11.2 percent lost their jobs after having a baby. More than one third of the surveyed women believed that male employees have more opportunities for getting promotion. Gender inequality in China subsided significantly under the egalitarian policies spearheaded by its leader, Mao. For instance, in the 1950s women won the right to own property and land, as well as the right to vote. Women gained the freedom to marry and divorce for the first time in Chinese history after a marriage law was passed in 1950. The female labor force participation rate soared, with more women becoming government leaders and role model workers in state-owned enterprises.

Germany based on the United Nations Development Program's (UNDP) gender inequality index), is associated with an average 1.9 percentage-point higher female labor share in its affiliates, after controlling for 4-digit industry and province fixed effects. These results remain robust even after controlling for a wide range of firm characteristics, including skill intensity and various measures of technology.

Perhaps more surprisingly, multinational firms appear to influence domestic firms' attitudes toward female workers, as evidenced by the finding that both domestic firms' average female labor share and likelihood of having a female manager increase with the prevalence of multinational firms in the same industry or city. Such correlation is robust to the control of the intensity of competition in the same industry or city, and does not appear to be caused by foreign firms' sorting into regions with lower female wages. In particular, after controlling for firm fixed effects and the determinants of firms' female employment based on existing studies, we find that a one standard-deviation increase in multinationals' output share in the same city (industry) is associated with an average 1.7 (0.7) percentage-point higher domestic firm's female labor share. Such cultural spillovers from multinationals are stronger if the FDI source is from a more gender-equal country, suggesting that the changes in domestic firms' female labor shares are not solely driven by the changing economic conditions in the labor or goods market.

To guide our empirical analysis on firms' cultural transfers and spillovers, and to quantitatively assess the effects of gender biases and the cultural effects of FDI on aggregate efficiency, we build a parsimonious multi-sector task-based model based on Acemoglu and Autor (2011), which features firm heterogeneity in productivity and biased perceptions about female labor costs. In the model, workers of the same gender have identical productivity, while women have a comparative advantage in skill- rather than physically-intensive tasks. Firms sell horizontally differentiated varieties in monopolistically competitive sectors, which differ in the intensity of skilled tasks. With female workers' completely specialized in supplying skills, production functions micro-founded on tasks with varying skill intensities can then be expressed as Cobb-Douglas production functions with constant cost shares for female and male labor.

We incorporate in this set up firms' taste-based discrimination, à la Becker (1957). Specifically, each firm draws its own subjective variable cost of female labor and productivity from two separate distributions, before entering a market. Countries with a more gender-equal culture are represented by distributions of firms' subjective female labor costs that have lower mean and variance. Biased perceived costs of female workers, compared to the objective benchmark, cause firms to employ fewer female workers, thereby lowering profits. Indeed, we find in our data a positive correlation between firms' time-varying profits and its female-to-male labor ratios, even when firm fixed effects are controlled for. These findings imply that gender discrimination is costly.

We model cultural spillovers as a process of domestic firms updating their (biased) beliefs about the cost of female workers towards the objective benchmark, similar to the models of cultural transmission model by Bisin and Verdier (2000, 2011) and Fernandez (2013). In the model, a domestic firm updates its prior belief about the cost of female workers when its prior differs from the average belief among foreign firms it interacts with. The extent of prior updating is stronger when there are more foreign firms with which the firm interacts. Cultural transfers and spillovers are also more significant in female labor-intensive industries (i.e., where women have a comparative advantage in production), in which gender discrimination is more costly. These model predictions about cultural spillovers are supported by our firm-level regression results. In the appendix, we show that the same set of theoretical predictions can be obtained in an alternative model with statistical discrimination, as in Phelps (1972) and Arrow (1973).

The last part of the paper quantifies the aggregate productivity losses due to gender discrimination, and the gains associated with the cultural effects of FDI. We apply the average revenue product approach proposed by Hsieh and Klenow (2009) in the context of our model, along with data on female labor shares across U.S. industries. Specifically, when we eliminate gender discrimination altogether by setting all firms' female-to-male labor ratios to the corresponding U.S. benchmark in the corresponding industry, we find that China's aggregate manufacturing total factor productivity (TFP) will increase by about 5%, compared to a 33% TFP gain by removing all capital distortions. Moreover, the cultural effect of FDI is estimated to reduce the dispersion of firms' female-to-male employment ratios within industries, hence contributing around 1% of the increase in China's aggregate manufacturing TFP.

This paper contributes to several strands of literature spanning broad social science disciplines. First and foremost, it adds to a large body of work in sociology and anthropology on the relation between globalization and culture (e.g., Hofstede, 1980; Pieterse, 2003; Hopper, 2007),[5] by offering empirical support for the theories or case studies about the "cultural convergence" hypothesis.

It is related to the economics literature on culture. Economists have identified systematic differences in social norms and people's beliefs across countries, and related them to various microeconomic phenomena, such as saving, participation in the financial market, investment

[5]Social psychologist Hofstede (1980) show how a country's culture is multi-dimensional and determined by both internal and external forces. Sociologists Pieterse (2003) and Hopper (2007) study how economic globalization can change participating countries' cultures. They examine three paradigms: the "clash of civilizations", "McDonaldization" and "hybridization".

in education, and preferences for redistribution (Guiso, Sapienza, and Zingales, 2006; Fernandez, 2011), as well as macroeconomic outcomes, such as economic growth (Gorodnichenko and Roland, 2017), trade and FDI between countries (Guiso, Sapienza, and Zingales, 2009). Recent research empirically examines channels through which cultural values can be transmitted from one country to another (e.g., Fisman and Miguel, 2007; Maystrea et al., 2014). Related to gender norms specifically, research shows that progress has been slow as prejudices against certain groups in society often have their deep historical roots (Jayachandran, 2015). Such hypothesis has been empirically verified by Alesina, Giuliano, and Nunn (2013), who show that the descendants of societies that practiced plough agriculture more intensively in the past have less equal gender norms today. Our paper illustrates how economic globalization can in fact fairly quickly change the exposition of gender norms.[6]

Given our focus on firms' revealed preferences for female labor, it relates to the extensive literature on gender discrimination (e.g., Altonji and Blank, 1999; Bertrand, 2011; Duflo, 2012). Becker (1957) in his classic work hypothesized that discriminatory firms will be driven out of business in the long run through market competition. Several studies have empirically verified Becker's hypotheses in the context of trade (Borjas and Ramey, 1995; Black and Brainerd, 2004; Juhn, Ujhelyi, and Villegas-Sanchez, 2014).[7] Recent research attempts to quantify the cost of discrimination (Hsieh et al., 2019; Cavalcanti and Tavares, 2016). For example, Hsieh et al. (2019) find that improved allocation of talent over the past few decades across gender and racial groups can explain about a quarter of the U.S. aggregate output growth per worker between 1960 and 2008 [8] Complementing their findings, we provide the first piece of firm-based quantification of the economic cost of discrimination and the cultural effect of FDI through reducing gender inequality.

Our paper is also related to an emerging literature that examines how home country characteristics affect foreign affiliate outcomes. Setzler and Tintelnot (2019), by using employer-employee matched data for the U.S., find that FDI from high-income countries tend to hire

[6]Kodama, Javorcik, and Abe (2018) also find that in Japan, the share of women in overall employment as well as in the management staff are on average higher, while the gender wage gap is smaller in foreign affiliates than in domestic firms. Foreign affiliates also tend to implement female-friendly human resource policies. In a recent working paper, Choi and Greaney (2019) use Korean data and find that multinationals from more gender-equal countries have higher female shares of employment and a higher chance of having a female CEO of their Korean affiliate. Our paper goes beyond the cultural transfer effects by studying, both theoretically and empirically, the mechanism of cultural spillovers and the associated productivity gains.

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

[8]A report by the McKinsey Global Institute (2015) illustrates the economic cost of gender biases in different countries. Using Japanese firm data, Kawaguchi (2007) finds that the impact of gender discrimination on firm profits and growth is small.

more skilled workers and pay a larger wage premium. Hjort, Li, and Sarsons (2020) show that changes in the minimum wages in the FDI source countries could affect the pays of their foreign subsidiaries. Gong (2020) finds that U.S. state-level R&D tax credit policies affect the technology transfer and spillovers of U.S. multinationals' subsidiaries in China.

Finally, our paper contributes to the extensive literature on the effects of FDI on the host countries. Existing studies of FDI spillovers focus almost exclusively on knowledge and technology spillovers (e.g., Aitken and Harrison, 1997; Javorcik, 2004; Keller and Yeaple, 2009; Lin et al., 2009; Keller, 2010). We explore whether and how FDI may transfer culture and shape social norms in the host countries. Our findings suggest that the gradually closing gender gap in some developing countries could be partially attributed to a previously unexplored aspect of FDI – gender cultural spillovers.[9]

The rest of the paper proceeds as follows. Section 2 introduces our theoretical model. Section 3 discusses our data source and measurements. Based on our theory, Section 4 tests the main model predictions about the transfer and spillovers of gender cultural values from multinationals. Section 5 quantifies the aggregate productivity loss due to gender discrimination and the aggregate efficiency gain associated with the cultural spillovers from FDI. The last section concludes.

2 Model

To guide our empirical analysis on cultural transfers and spillovers and quantify firm and aggregate efficiency losses due to gender biases, we build a parsimonious multi-sector task-based model with firm heterogeneity in productivity, biases towards female workers, and learning within sectors or regions. We outline the key features and results of the model in the main text, relegating all technical details and proofs to the appendix.

2.1 Set-up

2.1.1 Environment

Consider an economy with a three-layer structure: industries (sectors), firms, and tasks. The economy is endowed with M male workers and F female workers, who have identical

[9] The FDI technology spillover literature (e.g., Keller, 2010) distinguishes the spillovers to local firms in the same industry (horizontal spillovers) from the spillovers to local firms in upstream or downstream industries (vertical spillovers). In this paper, we only consider horizontal spillovers. Both horizontal cultural spillovers and horizontal technology spillovers should happen through similar mechanisms, such as through demonstration and labor turnovers. However, vertical spillovers are very different. In the case of technology spillovers, foreign firms have incentives to teach new technology to their local suppliers or buyers. They may not have the same incentive to transfer culture.

preferences. Consumers consume goods based on a Cobb-Douglas utility function with constant expenditure shares θ_j over industries indexed by $j = \{1, 2, ..., J\}$. Within an industry, consumers have Dixit-Stiglitz preferences with constant elasticity of substitution (CES) between varieties equal to $\sigma > 1$. Upon paying fixed costs to operate in an industry, firms sell horizontally differentiated varieties in the monopolistically competitive market, with each firm facing an isoelastic demand curve

$$y_{ij} = A_j p_{ij}^{-\sigma}, \tag{1}$$

where A_j is the demand factor of industry j and p_{ij} is the price of the variety sold by firm i in industry j.[10]

2.1.2 Labor Supply

The supply side of the model is built on Acemoglu and Autor's (2011) Ricardian model of the labor market. Each worker has one unit of time and has to decide how to allocate the time on supplying skilled and physically intensive (brawn) labor units in order to maximize labor income. Workers of the same gender have identical productivity, while women's *relative* productivity in skill-intensive tasks are higher than men, as assumed by Pitt, Rosenzweig, and Hassan (2012).[11]

In the appendix, we show that the no-arbitrage wage condition implies that female workers will allocate all their time to supply only skills, while male workers will supply only brawn. The idea is that wages will adjust to reflect workers' comparative advantages, in the same way that prices adjust to reflect countries' comparative advantages in the standard Ricardian trade model. In equilibrium, both female and male workers will therefore completely specialize in what they are relatively better at.

2.1.3 Production

On the demand side of the labor market, while we can simply assume that industries vary in female labor intensity, as in Do, Levchenko and Raddatz (2016), we choose to develop the micro-foundation of each sector's production function based on a task-based model of Acemoglu and Autor (2011) (see the appendix for details).

[10] $A_j = E_j P_j^{\sigma_j - 1}$, where E_j is the aggregate expenditure on industry-j goods.

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

Consider an economy in which every firm needs to employ skilled and brawn labor inputs to produce a continuum of different tasks, which it combines to produce final goods based on an industry-specific Cobb-Douglas production function. While tasks vary in skill intensity, industries differ in their relative dependences on skill-intensive tasks. The appendix shows how to derive a Cobb-Douglas production function with constant cost shares of skilled and brawn inputs from a task-based model. The basic idea is that a firm decides whether to use either skills or brawn to produce each task. Female workers, who are endowed with relatively more skills, will completely specialize in supplying skills, while male workers will completely specialize in supplying brawn inputs. In equilibrium, given prices for skills and brawn inputs, all tasks above a certain skill intensity cutoff are always produced with skills only, while tasks below that cutoff are always produced with brawn only. As such, industries that are relatively more dependent on skill-intensive tasks will be female labor-intensive.

We can then express the production function of firm i in industry j as

$$y_{ij} = \varphi_i f_{ij}^{\beta_j} m_{ij}^{1-\beta_j}, \tag{2}$$

where φ_i is firm i's total factor productivity and β_j is the industry-specific cost share of female workers. Firms are heterogeneous in productivity. Before entering a market, a firm draws φ_i from a normal distribution. Let us now suppress both firm and industry subscripts for notational ease.

2.2 Costs of Discrimination

2.2.1 Effects on Female-to-Male Labor Ratio

A novel feature of our model is that some firms hold biased views about women and employ suboptimal levels of female workers (as well as male workers). According to Becker's (1957) taste-based discrimination model, the employers of these firms act as if there is an additional wage cost associated with female workers. Similar to Becker's model, in our setting firms differ in their perceived variable costs of female labor. We further assume that the perceived total wage cost of female labor $1+\gamma$ follows a log-normally distribution over the entire real line, with mean $\psi \geq 0$ and variance $\nu > 0$:

$$\log(1+\gamma) \sim N(\psi, \nu).$$

Following Phelps's (1972) seminal paper, we assume that firms from countries with a more biased gender culture draw beliefs from a distribution with both higher ψ and ν.[12] The idea that the variance of $1+\gamma$ is increasing in the degree of a country's prejudice against women originates from the literature on statistical discrimination, which typically assumes that a firm's discrimination arises from its uncertainty about the cost or productivity of the discriminated group of workers.[13] If a country has no prejudice against women or men, it has $\psi = \nu = 0$.

Why would a firm, even when losing profits, only adjust the value of γ slowly? There are abundant examples about why people's perceptions about certain groups in society are often shaped by simple rule-of-thumb decisions. For instance, Alesina, Giuliano, and Nunn (2013) postulate that it takes a long time for agents to potentially realize the cost of their suboptimal choices due to prejudices.[14]

Upon drawing a parameter bundle (φ, γ), a firm has revenue equal to $R = A^{1-\eta}\left(\varphi f^{\beta} m^{1-\beta}\right)^{\eta}$, with A summarizing all sector-specific factors that affect the firm's market demand, taken as given by firms, and $\eta = 1 - \sigma^{-1}$.

Firm's profit function equals its revenue minus actual variable and fixed costs:

$$\pi = R - w_f f - w_m m - \phi, \tag{3}$$

where ϕ is the fixed cost measured in the final consumption aggregates. However, a biased firm maximizes its profit by choosing labor from both genders, taking into account the *expected* variable cost of female workers, γ:[15]

$$\max_{f,m} \pi^e(\varphi, \gamma) = \max_{f,m}\{R - w_f\left(1+\gamma\right) f - w_m m - \phi\}, \tag{4}$$

An unbiased firm has $\gamma = 0$, while a firm that favors female workers has $\gamma < 0$. The first order conditions of the problem imply the following firm's female-to-male labor ratio:

$$\frac{f}{m} = \frac{\beta}{\left(1-\beta\right)\left(1+\gamma\right)} \frac{w_m}{w_f}. \tag{5}$$

[12] A higher average γ can deliver outcomes that are consistent with gender biases at the firm level. However, in the data, we observe a significant variation in female-to-male labor ratios across firms even within a narrow industry.

[13] See Fang and Morro (2010) for a summary of the literature on statistical discrimination.

[14] Becker (1957) also postulates that when the whole society (all firms) holds the same prejudice, market competition will not drive the discriminating firms out of business.

[15] Notice that a firm can well have a preferences towards women. In that case, $\gamma < 1$. In theory, γ can take any positive or negative values over a real line, like the factor cost distortions in Hsieh and Klenow (2009). That does not mean that the actual profit will be infinite when the perceived γ is negative infinity. The actual (not perceived) profit will be infinitely negative (see below).

In the absence of gender biases (when $\gamma = 0$), the unbiased female ratio should be $\frac{\beta}{1-\beta}\frac{w_m}{w_f}$.

All else equal, a firm's female ratio is decreasing in γ, especially in the female intensive industries (β). This can be seen from the facts that

$$\frac{\partial}{\partial\gamma}\left(\frac{f}{m}\right) < 0; \frac{\partial^2}{\partial\gamma\partial\beta}\left(\frac{f}{m}\right) < 0.$$

Consider two FDI's countries of origin (c and c'), with country c having a more gender-equal culture represented by $\psi_c < \psi_{c'}$ and $\nu_c < \nu_{c'}$. We should expect that a firm from country c, due to a lower expected γ, has a higher average $\frac{f}{m}$. Let us summarize these results in the following proposition.

Proposition 1 *Firms from countries that hold a more biased view about female labor costs (i.e., a higher ψ) have a lower average female-to-male labor ratio within an industry. The relationship is quantitatively stronger in the more female labor-intensive industries (a higher β).*

Proof: See the appendix.

2.2.2 Discussion on Statistical Discrimination

Although discrimination is assumed to be taste-based, the results about the female-to-male labor ratio in (5) can be derived from a model with statistical (information-based) discrimination. In the appendix, we show a different version of the model that features statistical discrimination. In that model, firms draw different perceived female productivity parameters from a known distribution, instead of drawing female labor cost parameters. Under the intuitive assumptions that firms in countries with a stronger bias against women hold beliefs associated with a lower average but a higher variance (uncertainty) of perceived female labor productivity, eq. (5) will take a similar form but with a firm-specific β_i, which is decreasing in the firm's bias against women. In other words, regardless of the type of discrimination, our model predicts a negative correlation between firms' gender biases and their female labor shares.

2.2.3 Effects on Firm Profits

We now examine the effects of gender discrimination on firm and aggregate economic outcomes, respectively. Substituting the firm's privately optimal choices of female and male workers into its production and revenue functions yields firm output and revenue as[16]

$$
\begin{aligned}
y(\varphi,\gamma) &= A\left[\frac{\eta\varphi D}{c(\gamma)}\right]^{\sigma}; \\
R(\varphi,\gamma) &= A\left[\frac{\eta\varphi D}{c(\gamma)}\right]^{\sigma-1},
\end{aligned}
\tag{6}
$$

where $D=\beta^{\beta}(1-\beta)^{1-\beta}$ and $c(\gamma)=w_f^{\beta}(1+\gamma)^{\beta}w_m^{1-\beta}$. Since $c(\gamma)$ is increasing in γ, it is obvious that a firm's output and revenue are both decreasing in γ.

Substituting them into the *actual* profit function (3), we have

$$
\pi(\varphi,\gamma)=A(\eta D)^{\sigma-1}\left[\frac{\varphi}{c(\gamma)}\right]^{\sigma-1}\left[1-\eta\left(1-\frac{\gamma\beta}{1+\gamma}\right)\right]-\phi. \tag{7}
$$

In the appendix, we show that its profit is also decreasing in γ, which is summarized in the following proposition.

Proposition 2 *All else being equal, firms that are more biased against women have lower output, revenue, and profits.*

Proof: See the appendix.

2.2.4 Effects on Aggregate Productivity

Even when taste-based discrimination does not directly affect wages, prices need to adjust ex post to equalize the supply and demand for each firm's goods, according to the *subjective* cost of employing female workers and thus a suboptimal (from the economic or social point of view) level of female employment. Using the firm's demand curve (1) and $y(\varphi,\gamma)$ from (6), we can solve for its price and revenue TFP (TFPR) as

$$
\begin{aligned}
p(\varphi,\gamma) &= \frac{c(\gamma)}{\varphi\eta D}; \\
TFPR(\gamma) &= p(\varphi,\gamma)\varphi=\frac{c(\gamma)}{\eta D}.
\end{aligned}
$$

A higher γ, through increasing the variable cost of production, raises $p(\varphi,\gamma)$ and $TFPR(\gamma)$. Intuitively, a firm's biased view about female labor costs lowers its quantity supplied, thus raising its goods price. A higher TFPR may not imply a higher efficiency. On the contrary,

[16] Notice that the actual profit function: $\pi^e(\varphi)=R(\varphi,\gamma)-w_f f-w_m m-\phi$, is computed using the actual female wages, not the belief-distorted one.

it could arise from a more distortive view of factor costs. Readers who are familiar with the literature on resource misallocation (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009) should not be surprised about this assertion.

Hsieh and Klenow (2009) highlight a negative correlation between an industry's TFP and its dispersion of firms' TFPRs. The rationale is that in the absence of discrimination, firms' optimizations all set their TFPRs equal to the same constant, which depends on the industry's constant elasticity of substitution across varieties and a set of common factor prices. The fact that firms' TFPRs are more dispersed reflect more pronounced underlying distortions on factor prices. Under the assumption that discrimination and productivity are independently distributed, industry j's distorted TFP can be expressed as

$$\log TFP_j = \log TFP_j^e - \frac{\sigma\beta_j}{2}\nu_j, \tag{8}$$

where TFP^e is the efficient level of industry TFP when discrimination is absent (i.e., $\psi_j = \nu_j = 0$). All else being equal, an industry's TFP is lower if the dispersion of the discrimination factors (ν_j), the cost share of female workers (β_j), and/ or the elasticity of substitution between final good varieties (σ) are larger.[17] Finally, the economy's aggregate TFP, based on consumers' Cobb-Douglas utility function, can be expressed as $TFP = \prod_{j=1}^{J} TFP_j^{\theta_j}$.

Proposition 3 *A larger variation in firms' gender biases within an industry is associated with a lower industry TFP, thereby reducing aggregate TFP.*

Proof: See the appendix.

Our model focuses on gender discrimination as a cause of a higher dispersion of firms' TFPRs. However, there can be many different sources of distortions that deliver similar results, such as policy distortions on capital and output. Through the lens of our model, in Section 5 we will study the productivity losses due to gender biases, along with output and capital distortions.

2.3 Cultural Spillovers

The second part of our model studies whether multinational affiliates induce domestic firms to employ more women. Domestic firms may respond to higher FDI in the same market for two reasons - competition and learning (imitation). Regarding competition, the entry of foreign invested enterprises (FIEs) into a market may drive up input costs but lower final

[17]In Section 5, we will consider output and capital distortions, and permit correlations between all distortions in the computation of the productivity losses.

good prices. Both effects lower profits for all firms, possibly inducing some of them to employ more women. This is particularly true for the least productive firms who are concerned about survival.

We hypothesize that domestic firms, after observing the decisions and outcomes of FIEs in the same market (industry or city), will update their beliefs about female workers. Over time, domestic firms update their beliefs towards the "average" level of γ observed in their market, based on the FIEs they interact with. If there are more FIEs from countries with a less biased view about female workers, domestic firms' updates of their biased beliefs will be even larger.

Let us introduce the information structure under which domestic firms update their beliefs and in turn change their employment decisions. To illustrate the main theoretical points, we consider only one foreign country of origin.[18]

Consider a domestic firm that observes imperfectly FIEs' γ with noise in the same market (city or industry).[19] The "signal" the firm observes, z, can be expressed as

$$z = \psi^* + \varepsilon^* + \xi, \tag{9}$$

where ψ^* is the mean of the observed beliefs about $\log(1+\gamma)$, held by the FIEs from a foreign country (denoted by $*$). The parameter ε^* is a firm-specific female labor cost, relative to the mean, of FIEs. It is normally distributed with mean 0 and variance ν^*. We make no assumption about whether ψ^* is larger than ψ or not, nor about the inequality of their variances, ε^* and ε. FIEs in the same market may hold a more biased view against women, compared to domestic firms on average. The parameter $\xi \sim N(0, \upsilon_w)$ is an observational white noise, assumed to be distributed independently of ε^*. Therefore, from the firm's point of view, the error of the observed "signal" has two components: ε^* and ξ. To ease notations, let us define $\lambda^* = \varepsilon^* + \xi$ and rewrite (9) as

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

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

How does this signal help the domestic firm update its own belief? Based on $\overline{z}'s$ inferred from n neighbors, the firm updates its prior according to Bayes' rule. The posterior belief is

[18] Generalizing the model to consider multiple FDI countries of origin will only complicate the expressions without adding much to the main theoretical insights.

[19] The assumption that the firm observes its neighbors' female labor costs seems strong. Alternatively, we can make a more intuitive assumption that the firm observes its neighboring firms' female-male labor ratio, which the firm can then infer the subjective labor cost of an observed FIE as $1 + \gamma = \frac{m}{f} \frac{\beta}{1-\beta} \frac{w_m}{w_f}$.

normally distributed with the following mean ψ':[20]

$$\psi'(n,\overline{z}) \equiv E\left[\log(1+\gamma)\,|n,\overline{z}\right] = \delta(n,v,\omega^*)\,\overline{z} + (1-\delta(n,v,\omega^*))\,\psi, \tag{10}$$

where δ is the weight the firm puts on the observed (sample) mean $\overline{z} = \frac{1}{n}\sum_{l=1}^{n} z_l$, based on observed z's from n neighboring firms. According to DeGroot (2004), δ can be derived as

$$\delta(n,v,\omega^*) = \frac{nv}{\omega^* + nv}. \tag{11}$$

Partial differentiation yields the following comparative statics regarding the relationship between the number of neighbors and the average signal observed from FIEs:

$$\frac{\partial \psi'}{\partial n} = (\overline{z} - \psi)\underbrace{\frac{\partial \delta}{\partial n}}_{>0}. \tag{12}$$

Eq. (12) shows that the spillover effect is generally stronger if there are more FIEs whose signals are observed, as a firm will put a larger weight δ on other firms' signals about their beliefs and a smaller weight on its own prior belief. However, the direction of belief updating will depend on whether $\overline{z} < \psi$ or not. If the observed FIEs hold a less biased view toward women than the domestic firm itself (i.e., $\overline{z} < \psi$), a greater number of FIEs induces a larger extent of belief updating toward 0; while FIEs' more biased views observed by the firm (i.e., $\overline{z} > \psi$) will lead to belief updating away from 0, especially when there are more FIEs observed. The general theoretical results are summarized in the following proposition.

Proposition 4 *The average domestic firms' female labor share is decreasing in the observed average FIEs' belief in the cost of female workers ($\overline{z}$), more so if there are more FIEs in the same industry or city.*

Proof: See the appendix.

We know from eq. (8) that a higher dispersion of firms' TFPRs within an industry implies a greater extent of resource misallocation and thus a lower industry-level TFP. Our model shows that the dispersion of TFPRs will change, through firms' Bayesian updating based on the observed FIEs' behavior. Specifically, the posterior variance of a firm's γ, given n, v, and ω, can be expressed as

$$v'(n,v,\omega^*) = \frac{\omega^* v}{\omega^* + nv}, \tag{13}$$

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

which has the following properties:

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

The precision of the posterior $(1/v')$ increases with the number of neighbors revealing information about their beliefs. Moreover, if either the precision of the signal or that of the prior belief is lower, the posterior belief will be characterized with a larger variance.

To sum up, when FIEs in the same market are less biased against female workers (i.e., $\psi^* < \psi$ and $v^* < v$), they are more likely to employ proportionately more women than domestic firms. The presence of these FIEs in the same market induce the latter to increase their female employment. Such social learning leads to a change in social norms in the labor market, which we interpret as evidence of cultural spillovers. The opposite will be true if FIEs hold a less favorable view towards women (i.e., $\psi^* > \psi$ and $v^* > v$).

3 Data Sources and Summary Statistics

3.1 Firm-Level Data

The primary data for our analysis are drawn from the annual industrial firm surveys of China for the period of 2004-2007. The surveys, conducted by the country's National Bureau of Statistics (NBS), cover all state-owned firms and all non-state firms that have sales over 5 million RMB (about 0.7 million USD in the 2007 exchange rate).[21] Basic firm balance sheet information, such as output, value added, fixed asset, exports, employment, as well as industry code and ownership type (foreign or domestic in particular) are available. Despite the sampling threshold, the data are quite representative. Compared to the 2004 economic census, the aggregate data based on our firm data accounted for 91, 71, 97, and 91 percents of China's total industrial output, employment, exports, and fixed assets, respectively. To construct a panel data set, we use unique firm ID as well as firm contact information to identify identical firms across years.[22] We compute firm real capital stock and TFP, using the methods proposed by Brandt, Van Biesebroeck and Zhang (2012).

Most importantly, we use the following variables to construct a firm's female labor share, the main variable of interest in our regression analysis:

[21] We do not have firms in the service sector in our data. During our sample period, the FDI in the service sector was relatively small, compared to the manufacturing sector. According to China Statistical Yearbook 2005 (Table 18-17), in 2004 only 26% of the FDI inflow went to the service sector.

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

1. For 2004, we have information on firm employment by gender and education level. A worker is considered as skilled if s/he has education of high school or above. About 45 percent of total employment in our data set are considered skilled in 2004.[23]

2. For 2005, 2006 and 2007, we have information on employment by gender but not education levels.

The firm level patent data come from the State Intellectual Property Office. The data cover three main categories of patents: design (external appearance of the final product), innovation (fundamental innovations in methods) and utility model (e.g., changes in processing, shape or structure of products). In our measure of patents, we include all these three categories. We use the concordance table constructed by He et al. (2018) to merge our NBS firm data with the patent database.

Our firm data do not have information on workers' wages by gender. With this limitation, we focus on studying gender biases based on the varying female labor shares across firms.[24] A firm's foreign ownership status is identified based on its registration. We obtain information on FIEs' countries of origin from *Foreign Invested Firms Surveys* conducted by China's Ministry of Commerce (MOC). We then merge the country of origin data with the NBS firm survey data, using firm names and other contact information.

3.2 Identifying Managers' Gender

Prejudice against women can be more profound at higher levels of a firm's hierarchy (Bertrand and Hallock, 2001). This is often referred to as the "glass ceiling" effect, which stops women from getting promoted to senior-level management positions (Nevill et al., 1990). Do cultural spillovers also affect firms' appointment of female managers? To answer this question, we need information on the gender information of the manager of each firm. Unfortunately, the NBS industrial firm survey dataset only provides the names of the legal representatives, not their gender.[25] To get around this data limitation, we come up with a novel method to identify the gender of a firm's manager, based on the last character of the name of the legal representative in our data.[26] We use a 20% random sample of China's 1% population census

[23] An alternative definition of skilled labor is college and above. Under this definition, skilled labor accounts for 12 percent of the total employment in 2004. Our results are robust to this alternative definition.

[24] Wage information by gender is available in China's annual urban household surveys, which we use to assess the potential labor supply effects (See Table A6 in the appendix and Section 4.1 for details).

[25] The NBS industrial firm surveys of 1998-2000 provide the job title of the "legal person representatives", in addition to their names. About 84% of firms listed their general managers (or chief executives) as legal person representatives.

[26] A Chinese names usually starts with a last name, followed by a first name, which can have one or two characters. When a first name has two characters, the second character is more informative in terms of

in 2005, which contains 2.5 million names and their gender. 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:[27]

$$female\_prob_i = \frac{freq\_female_i}{freq\_female_i + freq\_male_i}, \tag{14}$$

where $freq\_female_i$ ($freq\_male_i$) is the number of times that character i appears as the last character in a female (male) name. Table A1 in the appendix lists the ten characters with the highest (lowest) female probability. For the top ten highest feminine characters, the probability that any of those characters is used in a male name is always less than 2%.

3.3 Country-Level Data

To measure a country's gender culture, we use the Human Development Report published by the United Nations Development Program (UNDP) in 2011.[28] The UNDP provides a set of indicators for gender inequality across 145 countries. We use the Gender Inequality Index (GII), which is a composite index capturing the loss of women's achievement due to gender biases. This index covers three aspects of a country's gender inequality, namely reproductive health, empowerment, and labor market participation. A higher GII indicates greater gender inequality. As Table A2 in the appendix shows countries with the lowest GII are European countries such as Sweden, Netherlands, Denmark, Switzerland and Norway. By contrast, countries with the highest GII are located in the Middle East and Africa. Obviously, a country's GII is correlated with its income level, but there are rich countries with very high GII (e.g. Saudi Arabia) and poor countries with low GII (e.g. the Philippines). In the regression analysis below, we will always control for countries' income levels. Since the GII indices are not available for the three ethnic Chinese FDI sources—Hong Kong, Macau, and Taiwan, we exclude firms that have the majority of equity owned by investors from these economies.[29]

femininity or maculinity. That is why we only focus on the last character of Chinese names.

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

[28] The reports have been published since 2008. We chose 2011 to maximize the coverage of countries.

[29] Given that the major populations of the three economies are ethnic Chinese, who are highly adaptive to the local culture, their measures of gender norms, even when available, may not be reflected in their employment practices in China. Moreover, whether we should treat the ethnic Chinese investments as FDI is subject for debate. Regardless, the data limitation forces us to drop FIEs with major investor from the ethnic Chinese economies, which account for about 48% of the FIEs in the 2004 cross section.

3.4 Industry-Level Data

We use three main industry-level variables in the regression analysis: female labor intensity, the import-output ratio, and the Herfindahl index. The last two were computed and aggregated based on China's Customs transaction-level data and NBS industrial firm data, respectively. See Table A3 in the appendix for details.

The key industry-level measure is female labor intensity, which we obtained from Do, Levchenko and Raddatz (2016). The data are originally taken from a publication titled "Women in the Labor Force: A Databook" by the US Bureau of Labor Statistics (BLS). It contains information on total employment and the female share of employment in each 4-digit industry (262 categories) defined by the US Census's Current Population Survey, covering both manufacturing and non-manufacturing sectors.[30] For each industry, we first take the average of the female labor shares across the sample years: 2004-2009. We then keep 77 manufacturing or mining sectors, and match each of them to a distinct NAICS 6-digit code (511 categories), using a concordance table available from the US Census website. Finally, we match a NAICS 6-digit code to a unique Chinese 4-digit industry code (CIC code), using a concordance table constructed by Ma, Tang and Zhang (2014). We then aggregate these measures up to the CIC 3-digit level (166 categories).[31]

Table A4 in the appendix lists the top 10 and bottom 10 industries in terms of female labor intensity (comparative advantage). The industries with the highest female labor share are apparel (0.65), leather products (0.60), fur accessories (0.60). In contrast, industries with the lowest female labor share include cement products (0.103), cement (0.103), and steel smelting (0.131). These industries all appear to depend more on physically-demanding tasks.

3.5 Summary Statistics of the Key Variables

Table 1 reports the summary statistics of the key variables used in the analysis (see Table A3 in the appendix for definitions of all variables used in the paper). Out of the 250,000 firms, the average firm female labor share is 0.41. Among the sub-sample of domestic Chinese firms (about 78% of the firm-year observations), the mean is 0.39, compared to 0.48 for FIEs (excluding Hong Kong, Macau and Taiwan's FIEs). FIEs also appear to be more likely

[30] Industries are classified based on the U.S. Census 2007 classification.

[31] Our empirical results are insensitive to using female labor intensity measures at the 2-digit level (29 categories). The estimated welfare gain of the counterfactual exercise that eliminates gender biases across firms within a 2-digit sector will be slightly larger. Obviously, the cost of using measures at a more aggregate industry level is that in our quantitative analysis, imposing the same factor intensities for all firms within a broad industry requires stronger assumptions. Since the original female labor intensity measures are available for 77 sectors, we think that the 3-digit CIC level is the most appropriate level of aggregation.

to appoint women as managers. Of all firms for which the name of the manager (legal representative) can be identified, the proportion of all firms that have a female manager is 0.25, compared to 0.24 for domestic firms and 0.26 for FIEs. Table 1 also reports the means and standard deviations for all variables used in the regressions, at the firm, industry and country levels.

Figure 1 plots the kernel density of female labor shares for both domestic firms and FIEs in 2004, showing that a significantly larger density of FIEs have a higher female-to-male labor ratio. To partially address the concern that FIEs are distributed unevenly across industries, due to differences in comparative advantages for instance, Figure 2 plots the kernel density of firms' female labor shares after demeaning them from their corresponding 4-digit industry averages. It confirms that the different distributions of female labor shares between domestic firms and FIEs are not driven by their varying prevalences across industries.[32]

4 Empirical Evidence

4.1 Cultural Transfers within Multinational Firm Boundaries

We first empirically examine Proposition 1, which is about the cultural transfers of multinational headquarters' gender norms to their affiliates in China. We use the 2004 cross-sectional sample, which allows us to control for skill intensity that is not available in other years. We estimate the following specification:

$$\left(\frac{f}{f+m}\right)_{ic} = \beta_0 + \beta_1 GII_c + \beta_2 \ln(GDP/Pop)_c + \mathbf{X}'_{ic}\boldsymbol{\gamma} + \{FE\} + \varepsilon_{ic}, \tag{15}$$

where $\left(\frac{f}{f+m}\right)_{ic}$ is the female share in employment of foreign firm i from country of origin c, or the probability that it has a female manager. GII_c is the gender inequality index of country c, as described in Section 3. Country c's (log) GDP per capita, $\log(GDP/Pop)_c$, is included as a regressor to control for any country-specific determinants of female employment that are related to the country's stage of development. The regression sample includes only FIEs. Thus, our identification comes from the variation in the gender norms of the multinationals' countries of origin.

The regressor $\mathbf{X}_{ij}$ is a vector of firm-level variables to control for the other determinants of firms' female employment proposed in the literature. To the extent that investments

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

in capital, technology, and automation in production reduce the demand for physically demanding tasks (Juhn, Ujhelyi, and Villegas-Sanchez, 2014), technology transfer from advanced economies and the associated investment by the affiliates may complement female labor. To address this concern, we include as controls the FIE's computer intensity, R&D intensity, log(1+number of patents), log(TFP) (measured by the Olley-Pakes method), and log(capital intensity) (see Table A3 in the appendix for definitions). In addition, we control for the firm's (log) wage rate to address the concern that FIEs may exploit the average lower wage among female workers due to gender biases in the labor markets, and (log) output to take into account any firm-level scale effect on female employment.[33]

FIEs may adapt to the local business culture over time. In their initial years of operation in China, they may bring along their home culture to the host country. Such cultural transfer, however, may dissipate over time if the affiliate starts to assimilate itself with the local culture and acts more like a domestic firm. We control for the potential assimilation effect by including the FIE's log(age) as a regressor. Finally, we include province and 4-digit industry fixed effects in $\{FE\}$. Province fixed effects control for any time-invariant local-labor-market factors that affect foreign firms' employment decisions, as China's social and economic environments differ substantially across regions. Industry fixed effects control for any unobservable industry heterogeneity that may affect firms' female labor shares, such as an industry's female comparative advantage. ε_{ic} is the error term.

The regression results reported in Table 2 provide strong support for Proposition 1. By controlling for province and 4-digit industry fixed effects but without any other firm covariates, we find in column 1 a negative and fairly significant (at the 5% level) correlation between multinationals' home countries' GII and their affiliate's female labor shares in China. In column 2, when a wide range of firm controls are included in addition to the fixed effects, the coefficient of GII becomes statistically significant at the 1% level. The estimated coefficient of -0.1 implies that a one-standard-deviation decrease in a country's GII (0.195, equivalent to changing Malaysia's GII to the level of Germany) is associated with a 1.9 percentage-point higher female labor share in that country's affiliates in China. Moreover, we find no evidence that the income level of the country of origin is related to its foreign affiliates' female employment. Firms' computer intensity, R&D intensity, patents and TFP are all negatively correlated with their female labor shares. In other words, our results show that among FIEs in China, technology does not appear to complement firms' female employment. Older FIEs hire proportionately more women on average, rejecting the

[33] For instance, if a larger firm requires more management inputs, and women have a comparative advantage in communication and management skills, then we should expect a positive correlation between a firm's size and its female employment share, something that our regression results confirm.

assimilation hypothesis in this context.

Column 3 uses the probability of the firm's having a female manager, as defined in Section 3.2, as the dependent variable. The reported negative and significant correlation between a FIE's GII and the likelihood that the firm appoints a female manager also supports Proposition 1.

In column 4, we add in the regression an interaction term between an industry's female labor intensity, measured using the U.S. data as described in Section 3.4, and the FIE's source country's GII. The coefficient on the stand-alone GII becomes insignificant, while the coefficient on the interaction term is negative and statistically significant, supporting the second part of Proposition 2 that the cultural transfers from multinationals are stronger in female labor-intensive industries. In sum, the results in Table 2 suggest that multinationals' cultural transfers are not a general feature of FDI. The culture of the country of origin matters.

We examine the robustness of our gender culture measure in Appendix Table A5, which replicates the regressions in Table 2 with an alternative measure of gender equal culture for each country. We follow Falk and Hermle (2018) to create a composite measure using a principle component analysis. In particular, we construct a gender equality index (CGEI) based on the following five indices: (1) the Global Gender Gap Index of the World Economic Forum in 2006; (2) the ratio of female to male labor force participation rates in 2005; (3) the number of years since women's suffrage in 2005; (4) the share of women in national parliaments in 2005; (5) the World Value Survey gender equality index in 2005, an average score of three questions in the survey (V44, V61 and V63) (see Table A3 in the appendix about each index's data source). The CGEI is simply the first principle component from a principle component analysis. A country with a higher value of CGEI tends to have a more equal gender culture. As shown in Table A5 in the appendix, our main results are robust to using this alternative measure of gender culture.

One may argue that the reason why FIEs employ more women than domestic firms is because of their intention to exploit the lower equilibrium wages of women, possibly due to gender discrimination in the labor markets (Siegel, Kodama, and Halaburda, 2014). Another alternative hypothesis is that women are attracted to move to locations where foreign firms are prevalent. Notice that either hypothesis implies a negative correlation between average female wages and the prevalence of FIEs across markets. Without information on wages by gender in the firm data, we rely on China's urban household survey data for the period of 2004-2007 to examine whether our results on cultural transfers are driven by either of the hypotheses. Table A6 in the appendix reports the regression results, showing a positive correlation between the female wage premium and FIEs' output share across cities, after controlling for the obvious determinants of wages. While these results imply no causality, they confirm that FIEs do not seem to be attracted to markets where female wages were lower, or that they depress female wages.

4.2 Firms' Female Labor Shares and Profits

We empirically examine Proposition 2 about a positive relationship between firms' profit and female labor shares. To this end, we regress a firm's profitability, defined as the ratio of profit to sales, on its female labor share, using the 2004-2007 panel data.[34] As is shown in column 1 of Table 3, we find a positive and statistically significant correlation between a firm's female labor share and profitability. Such result is obtained after firm and year fixed effects, as well as firm-level controls (R&D intensity, log(1+number of patents), capital intensity, log wage rate, log firm age, and log employment as in Table 2) are included as controls.[35] Column 2 shows consistent results when only domestic firms are included in the sample.

4.3 Cultural Spillovers from Multinationals to Domestic Firms

In this section we examine whether domestic firms' employment decisions can be influenced by FIEs. We adopt the empirical specification widely used in the literature on FDI spillovers (e.g., Aitken and Harrison, 1997; Javorcik, 2004), to explore the relationship between the prevalence of FDI and domestic firms' outcomes in the same market, defined as either an industry or a city.[36] The specification for estimating cultural spillovers is

$$\left(\frac{f}{f+m}\right)_{ik} = \gamma_0 + \gamma_1 FDI_k + \gamma_2 import_k + \gamma_3 Herf_k + \mathbf{X}'_{ik}\boldsymbol{\gamma} + \{FE\} + \varepsilon_{ik}, \tag{16}$$

where $\left(\frac{f}{f+m}\right)_{ik}$ is either the female labor share or the probability of having a female manager of *domestic* firm i. FDI_k is the output share of FIEs in market k.[37] $import_k$ and $Herf_k$

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

[35] We replace ln(output) by ln(employment) for this analysis as obviously, revenue and output are strongly correlated. As the goal is to control for the scale effect on profits (and female labor shares in the previous tables), using ln(employment) is a compromise. All results in this table remain robust when ln(output) is used as a control. The t-statistics of ln(output), if included, is very high. Results are available upon request.

[36] There are 345 prefecture-level cities in China.

[37] We exclude the Hong Kong, Macau and Taiwan invested firms when measuring the FIE share. The spillover effects are weaker but qualitatively similar when we include these firms. The estimation resrults are avaialble upon request.

are import-to-output ratio and Herfindahl index, respectively.[38] We include an industry's import-to-output ratio as a regressor to control for the possibility that import competition may reduce gender inequality by pushing the more discriminating firms to exit (Black and Brainerd, 2004). For the same reason, we also include an industry's Herfindahl index to control for any changes in market structure, possibly due to an increased prevalence of FIEs. To the extent that these measures capture the changes in the degree of market competition, any identified effect of FDI on firms' female labor shares should be above and beyond the standard competition effect.[39]

As often emphasized in the literature on FDI, domestic firms learn from FIEs about product designs, production technology, and foreign sales opportunities. These spillovers can be gender-biased. For instance, technology upgrading can increase the demand for female labor (Juhn, Ujhelyi, and Villegas-Sanchez, 2014). To partially control for the technology-induced effect on firms' employment, we include in the regressions various measures of technology, $\mathbf{X}_{ik}$, as we did in Table 2. $\{FE\}$ includes a host of fixed effects, which will be explained below.

We estimate eq. (16) using a sample of domestic firms only. We first report in Table 4 the regression results with markets defined as 4-digit industries, before reporting in Table 5 the results with markets defined as cities.[40] Based on the 2004 sample, column 1 of Table 4 reports that domestic firms' female labor shares are increasing on average with the share of output by FIEs in the same industry. We also find a negative coefficient on the Herfindahl index, consistent with Becker's (1957) hypothesis that increased market competition (as measured by a lower Herfindahl index) can reduce employers' discrimination. However, the negative correlation between the import-output ratio and domestic firms' female labor shares across industries cannot be explained by the same hypothesis. In column 2, we find that the probability of a domestic firm's having a female manager is positively correlated with the output share of FIEs across industries.[41] In particular, controlling for province fixed effects and a host of firm covariates, we find that a one standard-deviation increase in the FIEs' share in an industry's output (0.218; see Table 1) is associated with a 1.02 percentage-point increase in the likelihood that a domestic firm appoints a female manager.

[38] The HS 8-digit product level import data come from Chinese Customs, which we further aggregate into 4-digit industry level.

[39] Notice that it is difficult to quantitatively separate the competition effect from the cultural effect.

[40] The HS 8-digit product level import data come from Chinese Customs, which we further aggregate into 4-digit industry level.

[41] Since the managers (legal representative) of firms were not changed frequently between 2004 and 2007, we do not have enough variation to identify the potential positive correlation using the panel data after controlling for firm fixed effects. As a result, when the probability of the firm's having a female manager is used as the dependent variable, we use the 2004 cross-sectional sample for the analysis.

One may be concerned that the positive cross-industry correlation between domestic firms' female labor shares and FIEs' output shares simply reflects FIEs' self-selecting into industries, in which women have a comparative advantage. To address this concern, in columns 3 and 4, we use the 2004-2007 panel data so that firm fixed effects can be included to explore a firm's potential response to the changes in FIEs' prevalence in the same market. According to the results reported in column 3, domestic firms' female labor shares are positively correlated with FIEs' output share across industries, even after controlling for firm and year fixed effects. The correlation is economically significant – a one standard-deviation increase in FIEs' share in an industry's output is associated with an average 0.7 percentage-point higher female labor share among domestic firms in the same industry.

In column 4, we examine whether FDI from countries with lower gender inequality generates a larger spillover effect. In addition to the stand-alone output share by FIEs in the industry, we include an interaction term between FIEs' output share and the average measure of their gender norms, measured by the output-weighted average GII index. We find statistically significant coefficients with the expected signs on the interaction term in column 4. In sum, the cultural spillovers from FIEs documented so far appear to be mainly coming from multinationals whose home countries' culture is more favorable for women, supporting Proposition 4.

To verify if geographic proximity matters in cultural spillover, we include two FDI variables separately as regressors in the regression: the FIEs' share in the same industry and same province and the FIEs' share in the same industry but other provinces. It is evident in column 5 that the spillover effect is stronger when the FIEs are located in the same region. An F-test shows that the difference in the corresponding coefficients is statistically significant. These results support our theoretical hypothesis that an important mechanism through which FIEs' culture get diffused to local firms is by demonstration.

In column 6, we include an interaction term between the FIEs' share and the average profitability of FIEs in the same industry as an additional regressor. We find a positive coefficient on the interaction term, suggesting that domestic firms are more likely to imitate FIEs when the latter are more successful. This finding is consistent with the learning part of our theoretical model, which emphasizes that profit maximization is a key motivation for learning among domestic Chinese firms.

One may be concerned that different technology trends and speed of structural change (e.g., the increasing input shares of services) across Chinese industries may drive both the demand for female workers and FDI up. To partially address this concern, we include 2-digit sector-year fixed effects in column 7 as a robustness check. Our main results remain robust.

In Table 5, we measure the prevalence of FDI by the FIEs' output share in a city, instead of an industry. Similar to the results at the industry level reported in Table 4, we find that both domestic firms' female labor shares and probabilities of appointing female managers are positively correlated with FIEs' output share across cities, after controlling for firm and year fixed effects, as well as the average industries' import-to-output ratios and Herfindahl indices. Specifically, the coefficient of 0.092 in column 3 implies that a one standard-deviation increase in the FIEs' output share in the same city (0.182; see Table 2) is associated with an average 1.7 percentage-point increase in a domestic firm's female labor share.

In column 5, we observe that the spillover effect is stronger when the FDI is in the same city and same industry, compared to the FDI in the same city but other industries. However, an F-test statistic shows no statistically significant difference between the two corresponding coefficients. Similar to the results based on the variation across industries in the previous table, column 6 confirms that higher FIEs' profitability in the same city is positively correlated with the extent of spillovers, while column 7 shows that our main results are robust to the additional control of province-year fixed effects.

We conduct two more robustness checks. First, we measure the prevalence of FIEs by their employment share in the same industry to address the concern that the degree of spillovers is proportional to FIEs' employment rather than their sales. Second, we use the lagged FIEs' share of output in the same industry to partially address the usual simultaneity bias. The regression results remain robust to using these alternative measures, as reported in Table A7 and Table A8 in the appendix.

Two remarks are in order before we conclude this section. In both Table 4 and Table 5, if only the competitive pressure of FIEs matters, we would not be able to find a significant coefficient on the interaction term between FIEs' output share and their average home country's gender norms. Moreover, firms in the same city but different industries are unlikely to be competitors in the same final-goods market. Many FIEs in China are also export-oriented. The spillover effect from FIEs to domestic firms in the same city is unlikely to be all due to increased competition from FIEs.[42]

[42] The entry of foreign firms into a market may drive up input costs but lower final goods prices. In our model with heterogeneous firm productivity and discrimination factors, the more discriminating firms, due to resulting losses, are more likely to exit the market. We find in our data that firms with higher female labor shares are less likely to exit in response to an increase in FDI in the same market, supporting Becker's (1957) seminal hypothesis. Such adjustments raise firms' profits but more importantly, reduce the misallocation of resources at the industry and national levels, therefore raising aggregate efficiency. These regression results are available upon request.

5 Quantifying the Effects of Firms' Gender Discrimination on Aggregate TFP

In this section, we use the model developed in Section 2 to quantify the aggregate productivity loss due to gender discrimination and the productivity gain associated with FDI's cultural spillovers in China.

5.1 Quantifying the Productivity Loss due to Gender Discrimination

To account for the common sources of misallocation studied in the literature (i.e., capital and output distortions), we extend a firm's production function in Section 2 to one that also uses capital as a factor of production:

$$y_{ij} = \varphi_{ij} \left(f_{ij}^{\beta_j} m_{ij}^{1-\beta_j} \right)^{\alpha_j} k_{ij}^{1-\alpha_j},$$

where y_{ij} and k_{ij} stand for value added (after intermediate inputs are subtracted) and capital of firm i in industry j, respectively. α_j and β_j are industry j's cost shares of labor and capital in production.

For each unit of capital purchased, a firm pays $(1+\tau_{Kij})\, r$, where τ_{Kij} is a firm-specific capital distortion. Output distortion is modeled as a revenue tax (i.e., for each unit of value added created, a firm receives only a fraction $1-\tau_{Yij}$ of it).

We first focus on quantifying the efficiency loss due to resource misallocation in each industry. Using the average revenue product (ARP) approach proposed by Hsieh and Klenow (2009) to studying resource misallocation, the first-order conditions of firm i's profit maximization implies that the various firm-specific unobservable distortions can be measured with data as:[43]

$$\begin{aligned} 1+\tau_{Kij} &= \frac{1-\alpha_j}{\alpha_j \left(1-\beta_j\right)} \frac{w_m m_{ij}}{r k_{ij}}; && (17) \\ 1-\tau_{Yij} &= \frac{1}{\eta \alpha_j \left(1-\beta_j\right)} \frac{w_m m_{ij}}{R_i}; && (18) \\ 1+\gamma_{ij} &= \frac{\beta_j}{1-\beta_j} \frac{w_m m_{ij}}{w_f f_{ij}}. && (19) \end{aligned}$$

[43] See Section 3.1 for the details of each firm-level variable used to compute firm-level wedges. Following Hsieh and Klenow (2009), we drop 1 percent of the tails of the distributions of $\log(1+\tau_{Ki})$, $\log(1-\tau_{Yi})$, and $\log(1+\gamma_i)$, respectively.

According to Hsieh and Klenow (2009), a firm's $TFPR$ is proportional to the product of various wedges. By incorporating gender discrimination, together with output and capital distortions, firm i's $TFPR$ based on eq. (19) can be expressed as

$$TFPR_{ij} = \frac{w_m^{\alpha_j\left(1-\beta_j\right)} \left[\left(1+\gamma_{ij}\right) w_f\right]^{\alpha_j \beta_j} \left[\left(1+\tau_{Kij}\right) r\right]^{1-\alpha_j}}{\eta \left(1-\tau_{Yij}\right) \Lambda_j}, \tag{20}$$

where $\Lambda_j \equiv \alpha_j^{\alpha_j} \left(1-\alpha_j\right)^{1-\alpha_j} \beta_j^{\alpha_j \beta_j} \left(1-\beta_j\right)^{\alpha_j\left(1-\beta_j\right)}$.

We can quantify the productivity loss due to gender discrimination in industry j using the formula from Hsieh and Klenow (2009) as

$$TFP_j = \left[\sum_{i=1}^{N_j} \left(\varphi_{ij} \frac{\overline{TFPR}_j}{TFPR_{ij}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{21}$$

where φ_{ij} is firm i's TFP, $\overline{TFPR}_j$ is the weighted average of $TFPR_{ij}$, with weights equal to each firm's value added. N_j is the number of differentiated products.

We implement the following procedures to compute a firm's TFP and $TFPR$.

1. We first compute firm i's γ_i according to (19)

$$\gamma_{ij} = \frac{\beta_j}{1-\beta_j} \frac{w_m m_{ij}}{w_f f_{ij}} - 1.$$

   We set $w_f/w_m = 0.78$, according to the average wage premium for men reported in China's statistical yearbooks for the sample period (2004-2007). We set β_j for each of the 166 3-digit (CIC) industries based on the female labor shares for 77 manufacturing industries in the U.S., using data from the U.S. Population Census (see Section 3.4 and Table A4 in the appendix for details).

2. We obtain capital cost shares, $1-\alpha_j$, at the NAICS 6-digit level from the NBER-CES Manufacturing Industry Database. We use the concordance table and rules described in Section 3.4 to average them up to the 166 3-digit CIC industries. Since our industry classification is broader than that of Hsieh and Klenow (2009) (who consider over 400 4-digit industries), we impose $\sigma = 2$, instead of 3 as they did.[44] We then compute $1+\tau_{Kij}$ and $1-\tau_{Yij}$ based on (17) and (18), using these industry-level parameters and firm-level data on employment and capital costs.

[44] Imposing $\sigma = 3$ for each 3-digit industry will increase the estimated manufacturing TFP gains associated with removing all distortions by an order of magnitude larger than what Hsieh and Klenow (2009) find for China.

3. We then compute $TFPR_i$ using estimated γ_{ij}, $1+\tau_{Kij}$, $1-\tau_{Yij}$, as well as the aforementioned industry-level parameters, based on (20).

4. Finally, we compute firm i's TFP, based on the isoelastic demand curve described in Section 2.1, as

$$\varphi_{ij} = \kappa_j \frac{R_i^{\frac{\sigma}{\sigma-1}}}{\left(f_i^{\beta_j} m_i^{1-\beta_j}\right)^{\alpha_j} k_i^{1-\alpha_j}},$$

where κ_j is a constant, independent of misallocation or discrimination. It will drop out when we compute the ratio of distorted TFP to efficient TFP of each industry.

With all the components required to compute TFP_j according to (21) in hand, we conduct three counterfactual exercises. In the first exercise, we compute the ratio of an industry's TFP with all three types of distortions present to its efficient level (with firms' TFPRs equalized within the same industry), as follows:

$$\frac{TFP_j}{TFP_j^e} = \left[\sum_{i=1}^{N_j} \left(\frac{\varphi_{ij}}{\overline{\varphi}_j} \frac{\overline{TFPR}_j}{TFPR_i}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}, \tag{22}$$

where $\overline{\varphi}_j = \left[\sum_{i=1}^{N_j} \varphi_i^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$.[45] In the second exercise, we want to gauge the contribution of gender discrimination to an industry's efficiency loss. Therefore, we compute the ratio of the industry's TFP with output and capital distortions (but without gender distortions) to the efficient level of TFP, as follows:

$$\frac{TFP_j^{\gamma=0}}{TFP_j^e} = \left[\sum_{i=1}^{N_j} \left(\frac{\varphi_{ij}}{\overline{\varphi}_j} \frac{\overline{TFPR}_j^{\gamma=0}}{TFPR_i^{\gamma=0}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}}. \tag{23}$$

In the third exercise, we are interested in knowing the contribution of capital distortions to an industry's efficiency loss. The purpose of this exercise is to compare the contribution of gender discrimination with the main source of distortion studied in the literature. To this end, we compute the ratio of TFP with the presence of both output and gender distortions

[45] Following Hsieh and Klenow (2009), we drop 1 percent of the tails of the distributions of $\log\left(TFPR_i/\overline{TFPR}_j\right)$ and $\log\left(N_j^{\frac{1}{\sigma_j-1}} \varphi_i/\overline{\varphi}_j\right)$, respectively. We recalculate all the industries' averages after removing those outliers in the sample.

(but without capital distortions) to the efficient level of TFP:

$$\frac{TFP_j^{\tau_K=0}}{TFP_j^e} = \left[\sum_{i=1}^{N_j} \left(\frac{\varphi_{ij}}{\overline{\varphi}_j} \frac{\overline{TFPR}_j^{\tau_K=0}}{TFPR_i^{\tau_K=0}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}. \tag{24}$$

For each of the three scenarios, we then compute the corresponding ratios for the economy's manufacturing TFP in each year using the Cobb-Douglas aggregate: $\frac{TFP}{TFP^e} = \prod_{j=1}^{J} \left(\frac{TFP_j}{TFP_j^e} \right)^{\theta_j}$, where θ_j is industry j's value added share in the manufacturing sector.

Table 6 reports for each sample year the TFP gains $(100 \times (\frac{TFP^e}{TFP} - 1))$ by removing all three distortions, capital and output distortions, as well as gender and output distortions, respectively. Using formula (22)-(24), column 1 shows that removing all three types of distortions will bring about 100% and 96% aggregate TFP gains in 2004 and 2007, respectively. The gradual decline in the TFP gain reflects that the Chinese manufacturing sector has become more efficient over time. Column 2 shows that by eliminating capital and output distortions (keeping gender discrimination), the estimated TFP gain for the two years decline to about 95% and 91%, respectively. In other words, as reported in column 4, gender discrimination accounted for about 5% China's aggregate TFP loss during the sample period.

As a comparison, we report the associated TFP gain with output distortion and gender discrimination removed, keeping capital distortions. The resulting TFP gain is reduced significantly. As reported in column 5, capital distortions accounted for 29-34% of aggregate TFP loss during the sample period, about 6 times the productivity cost of gender discrimination.

5.2 Quantifying the Productivity Gain from Multinationals' Cultural Spillovers

We now quantify the contribution of the cultural effect of FDI. Recall that our model shows that when facing FIEs from countries with lower mean and variance of $\log(1+\gamma)$, domestic firms' Bayesian updating will result in a gradual reduction in the mean and the variance of their own $\log(1+\gamma)$. While the mean does not affect an industry's TFP based on the APR approach, a lower variance, according to (8), will imply a higher industry TFP.[46]

To show that the prevalence of FDI in an industry is related to the dispersion of $\log(1+\gamma)$, we regress the change in the standard deviation of the firms' estimated $\log(1+\gamma)$ on the

[46] With firms' endogenous entry and exit, the conditional mean of $\ln(1+\gamma)$ will be different between the efficient and distorted TFP. Thus, the changing mean of $\ln(1+\gamma)$ due to cultural spillovers will also matter.

change in the FIEs' share in a sector's output. We run these regressions over one, two, and three-year horizons, respectively. As reported in Table 7, there is a negative correlation between the two variables, with the correlation being statistically significant for the samples over the two- and three-year horizons. The lack of significance in the regression results based on a sample at the annual frequency may imply that learning takes time to be realized. Figure 3 illustrates a negative relationship between the change in the dispersion of firm $\ln(1+\gamma)$ and the change in the FIEs' output share between 2004 and 2007 across 3-digit industries.

Through the lens of our model, we can ask: what would happen to gender inequality and the associated TFP losses if the share of FDI in a sector was reduced to zero or by half in China during the sample period? Answering such question involves several simple steps of calculation. First, we know that based on the coefficient of -0.929 in column 3 of Table 7, if the average FIEs' output share was reduced from the sectoral average of 34% to 17% (half) and 0, respectively, the associated increase in the standard deviation of $\log(1+\gamma)$ will be around 0.16 and 0.32.[47] Given that the average standard deviation of $\log(1+\gamma)$ of a sector over the sample period (2004-2007) is about 1.67, such increases in dispersion of $\log(1+\gamma)$ are about 9.6% and 19.2% of the observed dispersions during the sample period, which will also be their respective contributions to the potential TFP loss due to gender discrimination.[48] In other words, the cultural spillover effect contributes about 1% (i.e., 19% of 5%) aggregate TFP gains during the sample period.

6 Concluding Remarks

We show how economic globalization can change the long-standing prejudice against women in a country. Specifically, we empirically study whether and how multinational firms transmit gender norms across countries. Using Chinese manufacturing firm data over the period of 2004-2007, we find that foreign affiliates whose home countries' culture is more gender-equal tend to hire proportionately more women and appoint female managers. Foreign firms, especially those from countries with a more gender-equal culture, also generate cultural spillovers to domestic firms, as revealed by a positive correlation between domestic firms' female labor shares and the prevalence of FDI across industries or cities. Our empirical results remain robust even after we control for firm fixed effects, as well as a wide range of time-varying firm characteristics.

[47] These numbers are obtained by computing $(-0.929) \times (-0.34) \approx 0.33$ and $(-0.929) \times (-0.17) \approx 0.16$, respectively.

[48] These numbers are obtained by computing $0.32/1.67$ and $0.16/1.67$ respectively.

To discipline our empirical analysis and quantify the aggregate efficiency loss associated with gender discrimination and the cultural effects of FDI, we build a parsimonious multi-sector task-based model that features firm heterogeneity in productivity and biases towards female workers, as well as women having a comparative advantage in skill- rather than physically-intensive tasks. Consistent with the model predictions, we find evidence that domestic firms respond to increased FDI by employing more women, likely due to imitation. Such cultural spillovers are stronger in the more female labor-intensive industries. We also find that discriminating firms sacrifice profits.

Through the lens of our model, we quantify the aggregate TFP loss due to discrimination against women, and the extent FDI has alleviated that in China. Eliminating gender discrimination altogether is associated with a roughly 5% increase in aggregate manufacturing TFP. The cultural effect of FDI, through changing gender norms, is estimated to have contributed a 1% increase in aggregate manufacturing TFP. Our results reveal an under-explored externality of FDI, in addition to technology spillovers which have been the focus of the literature.

In recent decades, many developing countries have made important progress toward gender equality and women's empowerment. How much did FDI gender cultural spillover contribute to this success? Should we expect similar FDI cultural spillover in other developing countries with different historical, cultural and institutional background?[49] A deeper understanding of the mechanisms and pre-conditions of cultural spillover is needed, and we leave these important questions for future research.[50]

[49] For instance, an important study by Ross (2008) shows that oil-rich countries in the Middle East have lower female labor participation than their oil-poor counterparts, contributing to patriarchal norms and political institutions that slow down the progress toward gender equality.

[50] For example, if the spillover mechanism is through the labor turnover, then having a female labor force with enough human capital might be a pre-condition for this mechanism to function.

References

[1] Acemoglu, Daron, and David Autor (2011) "Skills, Tasks and Technologies: Implications for Employment and Earnings" *Handbook of Labor Economics*, Vol.4, pp. 1043-1171.

[2] Aitken, Brian, and Ann Harrison (1997) "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela" *American Economic Review*, 89(3), pp. 605-618.

[3] Alesina, Alberto, Paola Giuliano, and Nathan Nunn (2013) "On the Origins of Gender Roles: Women and the Plough" *Quarterly Journal of Economics*, 128(2), pp. 469–530.

[4] Alfaro, Laura (2017) "Gains from Foreign Direct Investment: Macro and Micro Approaches" *World Bank Economic Review*, 30, pp. S2–S15.

[5] Altonji, Joseph, and Rebecca Blank (1999) "Race and Gender in the Labor Market" in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics*, Vol.3C. Amsterdam: Elsevier.

[6] Arrow, Kenneth (1973) "The Theory of Discrimination" in Orley C. Ashenfelter and Albert Rees (eds.), *Discrimination in Labor Markets*, Princeton University Press.

[7] Becker, Gary (1957) *The Economics of Discrimination*, University of Chicago Press.

[8] Bertrand, Marianne (2011) "New Perspectives on Gender" in Orley Ashenfelter and David Card, eds, *Handbook of Labor Economics*, Vol. 4B, pp. 1545-1592.

[9] Bertrand, Marianne, and Kevin F. Hallock (2001) "The Gender Gap in Top Corporate Jobs" *Industrial and Labor Relations Review*, 55(1), pp. 3-21.

[10] Bisin, Alberto, and Thierry Verdier (2000) "Beyond The Melting Pot: Cultural Transmission, Marriage, And The Evolution Of Ethnic And Religious Traits" *Quarterly Journal of Economics*, 113(3), pp. 955-988.

[11] Bisin, Alberto, and Thierry Verdier (2011) "The Economics of Cultural Transmission and Socialization" in Jess Benhabib, Alberto Bisin and Matthew Jackson, eds, *Handbook of Social Economics*, Vol.1, North-Holland, pp. 339-416.

[12] Black, Sandra, and Elizabeth Brainerd (2004) "Importing Equality? The Effects of Globalization on Gender Discrimination" *Industrial and Labor Relations Review*, 57(4), pp. 540-559.

[13] Borjas, George, and Valerie Ramey (1995) "Foreign Competition, Market Power, and Wage Inequality" *Quarterly Journal of Economics*, 110 (4), pp. 1075-1110.

[14] Brandt, Loren, Jo Van Biesebroeck, and Yifan Zhang (2012) "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing" *Journal of Development Economics*, 97(2), pp. 339–351.

[15] Cai, Fang, Yaohui Zhao, and Albert Park (2008) "The Chinese Labor Market in the Reform Era" in Loren Brandt and Thomas Rawski, eds., *China's Great Economic Transformation: Origins, Mechanism, and Consequences*, Cambridge University Press.

[16] Cavalcanti, Tiago, and Jose Tavares (2016) "The Output Cost of Gender Discrimination: a Model-Based Macroeconomic Estimate" *Economic Journal*, 126, pp. 109-134.

[17] Choi, Jaerim, and Theresa Greaney (2019) "Global Influences on Gender Inequality: Evidence from Female Employment in Korea" Working Papers 201908, University of Hawaii at Manoa, Department of Economics.

[18] Dai, Mi, Wei Huang, and Yifan Zhang (2021) "How Do Households Adjust to Tariff Liberalization? Evidence from China's WTO Accession" forthcoming, *Journal of Development Economics*.

[19] DeGroot, Morris H. (2004) *Optimal Statistical Decisions*, John Wiley & Sons, Inc.

[20] Do, Quy-Toan, Andrei Levchenko, and Claudio Raddatz (2016) "Comparative Advantage, International Trade, and Fertility" *Journal of Development Economics*, 119, pp. 48-66.

[21] Duflo, Esther (2012) "Women's Empowerment and Economic Development" *Journal of Economic Literature*, 50(4), pp. 1051-1179.

[22] Falk, Armin, and Johannes Hermle (2018) "Relationship Between Gender Difference in Preferences to Economic Development and Gender Inequality" *Science*, 362, Issue 6412.

[23] Fang, Hanming, and Andrea Moro (2010) "Theories of Statistical Discrimination and Affirmative Action: A Survey" *Handbook of Social Economics*, Vol.IA, edited by Jess Benhabib, Alberto Bisin, and Matthew Jackson, North-Holland, pp. 133-200.

[24] Fernandez, Raquel (2013) "Cultural Change as Learning: The Evolution of Female Labor Force Participation Over a Century" *American Economic Review*, 103(1), 472-500.

[25] Fernandez, Raquel (2011) "Does Culture Matter?" in J. Benhabib, M.O. Jackson, and A. Bisin, editors, *Handbook of Social Economics,* Vol. 1A, North Holland.

[26] Fisman, Ray, and Edward Miguel (2007) "Corruption, Norms, and Legal Enforcement: Evidence from Diplomatic Parking Tickets" *Journal of Political Economy*, 115(6), pp. 1020-1048.

[27] Friedman, Thomas (1999) *The Lexus and the Olive Tree: Understanding Globalization*, Picador.

[28] Gong, Kaiji (2020) "The Local Technology Spillovers of Multinational Firms" Working Paper, Hong Kong University of Science and Technology.

[29] Gorodnichenko, Yuriy, and Gerald Roland (2017) "Culture, Institutions and the Wealth of Nations" *Review of Economics and Statistics*, 99(3), pp. 402–416.

[30] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2006) "Does Culture Affect Economic Outcomes?" *Journal of Economic Perspectives*, 20(2), pp. 23-48.

[31] Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2009) "Cultural Biases in Economic Exchange?" *Quarterly Journal of Economics*, 124(3), pp. 1095-1131.

[32] Harrison, Ann, and Andres Rodriguez-Clare (2010) "Trade, Foreign Investment, and Industrial Policy" in Dani Rodrik and Mark Rosenzweig, eds, *Handbook of Development Economics,* Vol.5, pp. 4039-4214.

[33] He, Zi-Lin, Tony Tong, Yuchen Zhang, and Wenlong He (2018) "A Database Linking Chinese Patents to China's Census Firms" *Scientific Data*, 5:180042.

[34] Hjort, Jonas, Xuan Li, and Heather Sarsons (2020) "Across-Country Wage Compression in Multinationals" NBER Working Paper 26788.

[35] Hofstede, Geert (1980) *Culture's Consequences: International Differences in Work-Related Values*, Sage Publications.

[36] Hsieh, Chang-Tai, and Peter Klenow (2009) "Misallocation and Manufacturing TFP in China and India" *Quarterly Journal of Economics*, 124(4), pp. 1403-1448.

[37] Hsieh, Chang-Tai, Erik Hurst, Chad Jones, and Peter Klenow (2019) "The Allocation of Talent and U.S Economic Growth" *Econometrica*, 87(5), pp. 1439–1474.

[38] Hopper, Paul (2007) *Understanding Cultural Globalization*, Polity.

[39] Huntington, Samuel P. (1996) *The Clash of Civilizations and the Remaking of Order*, Simon & Schuster.

[40] Javorcik, Beata Smarzynska (2004) "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages" *American Economic Review*, 94(3), pp. 605-627.

[41] Jayachandran, Seema (2015) "The Roots of Gender Inequality in Developing Countries" *Annual Review of Economics,* 7, pp. 63-88.

[42] Juhn, Chinhui, Gergely Ujhelyi, and Carolina Villegas-Sanchez (2014) "Men, Women, and Machines: How Trade Impacts Gender Inequality" *Journal of Development Economics*, 106, pp. 179–193.

[43] Kawaguchi, Daiji (2007) "A Market Test for Sex Discrimination: Evidence from Japanese Panel Data" *International Journal of Industrial Organization*, 25(3), pp. 441-460.

[44] Keller, Wolfgang (2010) "International Trade, Foreign Direct Investment, and Technology Spillovers", Chapter 19 in Handbook of the Economics of Innovation, Vol. 2, B. Hall and N. Rosenberg (eds.), Elsevier, North-Holland, 2010, pp. 793 – 829.

[45] Keller, Wolfgang, and Stephen Yeaple (2009) "Multinational Enterprises, International Trade, and Productivity Growth: Firm-level Evidence from the United States" *Review of Economics and Statistics*, 91(4), pp. 821-831.

[46] Kodama, Naomi, Beata S. Javorcik, and Yukiko Abe (2018) "Transplanting Corporate Culture across International Borders: FDI and female employment in Japan" *World Economy*, 41, pp. 1148–1165.

[47] Lin, Ping, Zhuomin Liu, and Yifan Zhang (2009) "Do Chinese Domestic Firms Benefit from FDI Inflow? Evidence of Horizontal and Vertical Spillovers" *China Economic Review*, 20(4), pp. 677-691.

[48] Ma, Yue, Heiwai Tang, and Yifan Zhang (2014). "Factor Intensity, Product Switching, and Productivity: Evidence from Chinese Exporters" *Journal of International Economics*, 92(2), pp. 349-362.

[49] Maystrea, Nicolas, Jacques Olivier, Mathias Thoenig, and Thierry Verdier (2014) "Product-Based Cultural Change: Is the Village Global?" *Journal of International Economics*, 92(2), pp. 212-230.

[50] McKinsey Global Institute (2015) *The Power of Parity: How Advancing Women's Equality Can Add $12 Trillion to Global Growth.*

[51] Melitz, Marc (2003) "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity" *Econometrica*, 71(6), pp. 1695–1725.

[52] Nevill, Ginny, Alice Pennicott, Joanna Williams, and Ann Worrall (1990) *Women in the Workforce: The Effect of Demographic Changes in the 1990s.* London: The Industrial Society.

[53] Phelps, Edmund S. (1972) "The Statistical Theory of Racism and Sexism" *American Economic Review*, 62(4), pp. 659-661.

[54] Pieterse, Jan Nederveen (2003) *Globalization and Culture: Global Melange.* Rowman & Littlefield Publishers.

[55] Pitt, Mark, Mark Rosenzweig, and Mohammad Nazmul Hassan (2012) "Human Capital Investment and the Gender Division of Labor in a Brawn-Based Economy" *American Economic Review*, 102(7), pp. 3531-3560.

[56] Restuccia, Diego, and Richard Rogerson (2008) "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments" *Review of Economic dynamics,* 11(4), pp. 707-720.

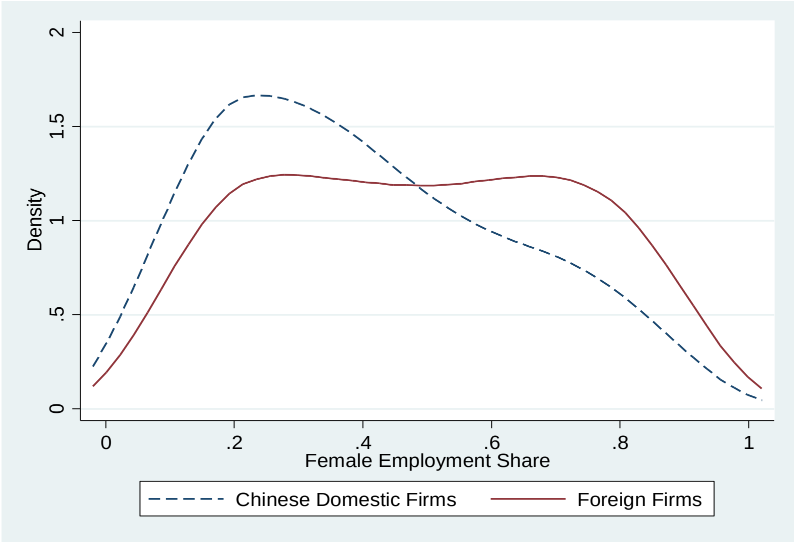
[57] Ross, Michael L. (2008) "Oil, Islam, and Women." *American Political Science Review*: 107-123.

[58] Setzler, Bradley, and Felix Tintelnot (2019) "The Effects of Foreign Multinationals on Workers and Firms in the United States" NBER Working Paper 26149.

[59] Siegel, Jordan, Naomi Kodama, and Hanna Halaburda (2014) "The Unfairness Trap: A Key Missing Factor in the Economic Theory of Discrimination" Harvard University Working Paper.

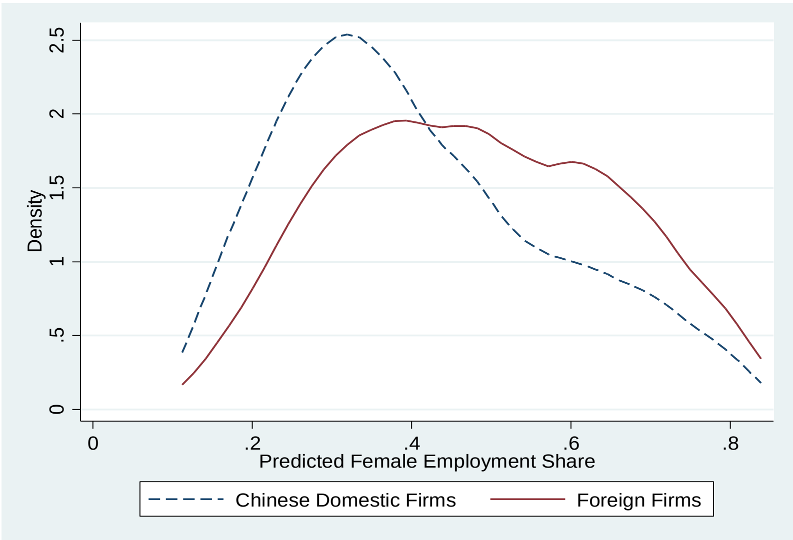
[60] Wei, Shang-Jin, and Xiaobo Zhang (2011) "The Competitive Saving Motive: Evidence from Rising Sex Ratios and Savings Rates in China" *Journal of Political Economy*, 119(3), pp. 511-564.

Figure 1: Distribution of Firms' Female Labor Share (2004)



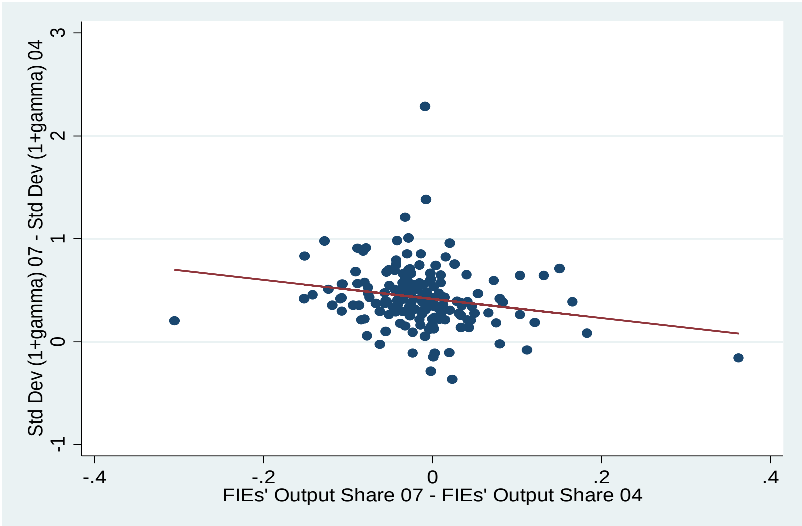
Source: NBS annual survey of industrial firms (2004) and authors' calculation.

Figure 2: Distribution of Firms' Female Labor Share (2004) (controlling for 4-digit Industry Fixed Effects)



Source: NBS annual survey of industrial firms (2004) and authors' calculation.

Figure 3: Long Diff in Standard Deviation of log(1+γ) and Multinationals' Output Share by Sector (2004-2007)



Source: NBS annual survey of industrial firms (2004) and authors' calculation.

Table 1: Summary Statistics of the 2004 Sample

Variable	Nb Obs	Mean	St Dev.
Firm Level			
Female employment share			
all workers	258,899	0.411	0.243
unskilled workers	240,787	0.437	0.299
skilled workers	255,239	0.370	0.230
domestic Chinese firms	202,536	0.390	0.236
foreign invested enterprises (FIEs)	28,450	0.482	0.256
Likelihood of a female manager			
all firms	217,181	0.246	0.277
domestic Chinese firms	170,501	0.243	0.277
foreign invested enterprises (FIEs)	23,243	0.255	0.273
Other firm characteristics used as regressors			
computer intensity	278,507	0.147	19.336
R&D intensity	272,948	0.031	0.054
ln(1+patent)	259,336	0.042	0.278
ln(TFP)	241,866	-0.972	1.071
skill intensity	258,899	0.454	0.293
capital intensity	255,449	100.879	1,046
output	275,460	72,743	656,030
profit rate	249,424	0.025	0.084
age	278,563	8.934	10.891
Country Level			
Gender inequality index	137	0.419	0.195
ln(GDP per capita)	137	8.060	1.671
Industry Level			
Female comparative advantage (3-digit)	166	0.309	0.110
Foreign output share (4-digit)	482	0.344	0.218
Herfindhal index (4-digit)	482	0.049	0.076
Import-output ratio (4-digit)	482	0.272	0.300
City Level			
Foreign output share (city)	345	0.155	0.182

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

Note: See definitions in Table A3 in the appendix.

Table 2: Gender Cultural Transfer

	(1)	(2)	(3)	(4)
Sample:	All Foreign Invested Firms in 2004			
Dependent Variable:	Female Share in Total Emp	Female Share in Total Emp	Prob. of Female Manager	Female Share in Total Emp
Gender inequality index (GII)	-0.057	-0.099	-0.122	0.015
	(-2.12)**	(-4.32)***	(-1.75)*	(0.26)
GII * Female comp. advantage				-0.305
				(-2.94)***
ln(GDP/pop)		0.003	0.005	0.001
		(0.89)	(0.79)	(0.17)
Controls	-	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y
Number of Obs.	12,345	11,504	7,884	10,693
Adj. R-sq	0.515	0.568	0.156	0.576

Notes: Firms' R&D intensity, skill intensity, computer intensity, ln(1+patent), ln(capital intensity), ln(TFP), ln(wage rate), ln (firm age) and ln(firm output) are included as control variables. t-statistics based on standard errors clustered at the country level are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Female Labor Share and Profitability

	(1)	(2)
Sample:	All Firms of 2004-2007 Panel	Domestic Firms of 2004-2007 Panel
Dependent Variable:	Profit/ Sales	Profit/ Sales
Female labor share	0.003	0.002
	(3.12)***	(1.74)*
Controls	Y	Y
Year fixed effects	Y	Y
Firm fixed effects	Y	Y
Number of Obs.	1,060,883	832,271
Adj. R-sq	0.542	0.549

Notes: Firms' R&D intensity, ln(1+patent), ln(capital intensity), ln(wage rate), ln(firm age) and ln(firm employment) are included as control variables. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Gender Cultural Spillover (Across Industries)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:	2004 Domestic Firms		2004-2007 Domestic Firm Panel				
Dependent Variable:	Female Labor Share	Prob. of Female Manager	Female Labor share				
$FDI_{industry}$	0.323	0.047	0.032	0.045		0.027	0.028
	(4.10)***	(3.42)***	(5.20)***	(4.21)***		(4.83)***	(4.37)***
$FDI_{industry\text{-}same\ province}$					0.095		
					(5.33)***		
$FDI_{industry\text{-}other\ provinces}$					0.026		
					(4.46)***		
FDI_{ind} x GII_{ind}				-0.049			
				(-3.33)***			
FDI_{ind} x $Profitability_{ind}$						0.143	
						(2.02)**	
Controls	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	-	-	-	-	-
Year FE	-	-	Y	Y	Y	Y	Y
Firm FE	-	-	Y	Y	Y	Y	Y
Sector-Year FE	-	-	-	-	-	-	Y
Number of Obs.	187,885	155,717	800,907	800,907	800,907	800,261	800,907
Adj. R-sq	0.138	0.046	0.754	0.794	0.754	0.754	0.759

Notes: $FDI_{industry}$ stands for the share of output by FIEs in a four-digit industry. $FDI_{industry\text{-}same\ province}$ stands for the share of output by FIEs in a four digit industry and in the same province. $FDI_{industry\text{-}other\ provinces}$ stands for the share of output by FIEs in a four digit industry and in other provinces. GII_{ind} is the weighted averages of the FIEs' home countries' GII, with weights equal to each FIE's output share in the industry. $Profitability_{ind}$ is the weighted average profitability of all FIEs in the industry. All regressions include R&D intensity, ln(TFP), ln(1+patent), ln(capital intensity), ln(output), ln(wage rate), ln(firm age), import/output ratio and Herfindahl index as control variables. The 2004 regressions include the control of skill intensity, which is not available in other years. See Table A3 in the appendix for the definition and construction of each variable. t-statistics based on standard errors clustered at the four-digit industry are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Gender Cultural Spillover (Across Cities)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample:	2004 Domestic Firms		2004-2007 Domestic Firm Panel				
Dependent Variable:	Female Labor Share	Prob. of Female Manager	Female Labor share				
FDI_{city}	0.095	0.048	0.092	0.108		0.078	0.061
	(4.57)***	(4.52)***	(5.17)***	(5.36)***		(4.99)***	(3.99)***
$FDI_{city\text{-}same\ sector}$					0.119		
					(5.89)***		
$FDI_{city\text{-}other\ sectors}$					0.088		
					(4.32)***		
FDI_{city} x GII_{city}				-0.152			
				(1.89)*			
FDI_{city} x $Profitability_{city}$						0.438	
						(2.27)**	
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	-	-	Y	Y	Y	Y	Y
Firm FE	-	-	Y	Y	Y	Y	Y
Province-Year FE	-	-	-	-	-	-	Y
Number of Obs.	187,885	149,594	765,457	765,457	765,457	763,881	765,457
Adj. R-sq	0.068	0.015	0.797	0.810	0.797	0.797	0.803

Notes: FDI_{city} stands for the share of output by FIEs in the same city. $FDI_{city\text{-}same\ sector}$ stands for the share of output by FIEs in the same city and same two-digit industry. $FDI_{city\text{-}other\ sectors}$ stands for the share of output by FIEs in the same city and in other two digit industries. GII_{city} is the weighted averages of the FIEs' home countries' GII, with weights equal to each FIE's output share in the industry. $Profitability_{city}$ is the weighted average profitability of all FIEs in the city. All regressions include R&D intensity, ln(TFP), ln(1+patent), ln(capital intensity), ln(output), ln(wage rate), ln(firm age), average import/output ratio and average Herfindahl index as control variables. The 2004 regressions include the control of skill intensity, which is not available for other years. See Table A3 in the appendix for the definition and construction of each variable. 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: TFP Gains by Removing Different Types of Distortions (%)

	(1)	(2)	(3)	(4)	(5)
	Aggregate TFP Gain by Removing			Contribution to Aggregate TFP by Removing	
Year	All Three Distortions	Capital and Output Distortions	Gender and Output Distortions	Gender Distortions	Capital Distortions
2004	100.26	95.26	66.24	4.99	33.93
2005	94.75	89.49	65.42	5.55	30.95
2006	96.79	91.49	68.38	5.47	29.35
2007	96.10	90.75	68.11	5.56	29.13

Notes: All numbers are 100x((TFP^e/TFP)-1), where TFP^e stands for the efficient level of aggregate manufacturing TFP with all distortions removed. TFP in column 1 is constructed by keeping all firms' distortions. TFP in column 2 is constructed by setting all firms' gender discrimination factors, γ, to 0, while TFP in column 3 is constructed by setting all firms' capital distortions, τ_K, to 0. The last 2 columns report the contribution of removing each type of distortions to China's aggregate TFP gain in each sample year.

Table 7: Correlation between FIEs' Output Share and the Dispersion of Firms' Gender Discrimination

	(1)	(2)	(3)
Sample:	2005-2007	2006-2007	2007
Dependent Variable:	$\Delta_{t,t-1}SD(\log(1+\gamma))$	$\Delta_{t,t-2}SD(\log(1+\gamma))$	$\Delta_{t,t-3}SD(\log(1+\gamma))$
$\Delta_{t,t-k}$FIE output share	-0.443	-0.689	-0.929
	(-1.31)	(-2.52)**	(-2.86)***
Number of Obs.	498	332	166
Adj. R-sq	0.004	0.025	0.043

Notes: Observations are at the sector-year level. $\Delta_{t,t-k}$ is an operator that takes the first difference of the variable of interest between year t and t-k. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A1: Ranking of Chinese Characters as the Last Character in Female and Male Names

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

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

Table A2: Country-Level Gender Inequality Indices

Rank	Country	Index	Rank	Country	Index
	Most Equal			Most Unequal	
1	Sweden	0.049	1	Yemen	0.769
2	Netherlands	0.052	2	Chad	0.735
3	Denmark	0.060	3	Niger	0.724
4	Switzerland	0.067	4	Mali	0.712
5	Norway	0.075	5	Congo	0.710

Source: Huamn Development Report 2011, United Nations Development Program (UNDP).

Table A3: Variable Definition and Data Source

Variable	Definition and Source
Computer intensity	Number of computers/total employment.
FDI_{city}	Output share of foreign invested firms in a city.
FDI_{ind}	Output share of foreign invested firms in a 4-digit industry.
Female comparative advantage	Female share in total employment by industry. Source: Do, Levchenko and Raddatz (2016) based on US Population Census Data.
Female labor share	Number of female workers divided by total employment.
Female probability of legal person representative	The probability of a Chinese character being the last character of a woman's name. It is calculated using equation (2) in the text.
Female share in unskilled labor	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 labor	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: Human Development Report 2011, UNDP.
Herfindahl index	Calculated from NBS annual industrial firm survey.
Import output ratio	Ratio of total imports to total domestic output at industry level.
ln(1+patent)	Number of firm level patents. Source: State Intellectual Property Office.
ln(age)	Natural log of the number of years since the start date of the firm.
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(GDP/pop)	Natural log of the GDP per capita in 2004. Source: World Development Indicators.
ln(output)	Natural log of total output.
ln(TFP)	Total factor productivity calculated with Olley-Pakes procedure.
ln(wage rate)	Natural log of total wage/total employment.
Number of years since women's suffrage in 2005	Inter-Parliamentary Union Website
Profitability	Total profit/sales.
Ratio of female to male labor force participation rates	Source: World Development Indicators.
R&D intensity	R&D expenditure/total value added.
skill intensity	Share of workers with high school and above education

Table A4: Top and Bottom 10 Three-Digit Industries Based on Female Comparative Advantage

Industry Code	Top 10 Industries	Female Labor Share	Industry Code	Bottom 10 Industries	Female Labor Share
181	Apparel	0.650	312	Cement Products	0.103
192	Leather Products	0.602	311	Cement	0.103
193	Fur Accessories	0.595	322	Steel Smelting	0.131
296	Rubber Shoes	0.563	323	Steel Rolling	0.131
191	Leather Accessories	0.563	324	Ferroalloy	0.131
182	Textile Shoes	0.563	321	Iron	0.131
183	Hat, Cap, and Millinery	0.563	334	Non-Ferrous Metall Alloys	0.150
176	Knit Fabric	0.561	201	Saw, Wood Chips	0.150
171	Cotton and Chemical Fiber	0.540	291	Automobile Tires	0.156
174	Silk and Thin Silk	0.538	361	Petroleum Special Equipment	0.163

Note: U.S. female share in total employment by sector. Source: Do, Levchenko, and Raddatz (2016).

Table A5: Gender Cultural Transfer with Alternatitve Gender Culture Measure

	(1)	(2)	(3)	(4)
Sample:	All Foreign Invested Firms in 2004			
Dependent Variable:	Female Share in Total Emp	Female Share in Total Emp	Prob. of Female Manager	Female Share in Total Emp
Composite gender equality index (CGEI)	0.051	0.065	0.032	0.013
	(3.14)***	(4.05)***	(2.47)**	(0.31)
CGEI * Female comp. advantage				0.223
				(5.12)***
ln(GDP/pop)		0.012	0.010	0.011
		(2.45)**	(2.64)***	(2.79)***
Controls	-	Y	Y	Y
Industry fixed effects	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y
Number of Obs.	10,962	9,495	7,884	9,495
Adj. R-sq	0.519	0.582	0.156	0.582

Notes: This table replicates the regressions in Table 2 with an alterenative measure of gender equal culture. See section 4 for the definition of CGEI. Firms' R&D intensity, skill intensity, computer intensity, ln(1+patent), ln(capital intensity), ln(TFP), ln(wage rate), ln (firm age) and ln(firm output) are included as control variables. t-statistics based on standard errors clustered at the country level are reported in the parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: The Impact of FDI on the Female Wage Discount by City

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

Notes: Data come from China Urban Household Survey. See Dai, Huang and Zhang (2021) for a detailed description of the UHS data. We conduct this exercise in two stages. In the first stage, we run individual level Mincer-type wage regressions for each city using the urban household data 2004-2007, and obtain the coefficient on the female dummy. We run this regression using all individuals and only those in the manufacturing sector. In the second stage, we run city-level regressions using the estimated female dummy from the first stage as the dependent variable. This table reports the regression results of the second stage. z-statistics based on bootstrapped standard errors are reported in the parentheses. FDI_{city} stands for the share of output by FIEs in the city. GII_{city} is the weighted average of the FIEs' home countries' GII, with weights equal to each FIE's output share in the industry. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A7: Gender Cultural Spillovers (FDI Prevalence Measured by Foreign Firms' Employment Share)

	(1)	(2)	(3)	(4)
Sample:	2004-2007 Domestic Firm Panel			
Dependent Variable:	Female Labor Share			
FDI	0.033	0.041		
	(3.12)***	(5.01)***		
FDI_{ind} x GII_{ind}		-0.032		
		(-3.31)***		
FDI_{city}			0.092	0.108
			(5.17)***	(5.36)***
FDI_{city} x GII_{city}				-0.152
				(1.89)*
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Number of Obs.	800,907	800,907	765,457	765,457
Adj. R-sq	0.754	0.794		0.794

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

Table A8: Gender Cultural Spillovers (All Regressors Lagged by One Year)

	(1)	(2)	(3)	(4)
Sample:	2004-2007 Domestic Firm Panel			
Dependent Variable:	Female Labor Share			
$FDI_{ind, t-1}$	0.027	0.060		
	(3.56)***	(4.76)***		
$FDI_{ind, t-1}$ x $GII_{ind, t-1}$		-0.093		
		(-5.01)***		
$FDI_{city, t-1}$			0.089	0.097
			(4.33)***	(4.47)***
$FDI_{city, t-1}$ x $GII_{city, t-1}$				-0.142
				(1.88)**
Controls	Y	Y	Y	Y
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Number of Obs.	684,304	684,304	713,334	713,334
Adj. R-sq	0.809	0.796	0.813	0.819

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

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

Heiwai Tang*
University of Hong Kong and Johns Hopkins University

Yifan Zhang†
Chinese University of Hong Kong

February 7, 2021

Abstract

This appendix provides proofs and additional theoretical results omitted in the main text.

*Corresponding author. Faculty of Business and Economics, University of Hong Kong, Pokfulam Road, Hong Kong. Email: tangecon@hku.hk.

†Department of Economics, Chinese University of Hong Kong, Shatin, Hong Kong. Email: yifan.zhang@cuhk.edu.hk.

1 Micro Foundation with a Task-Based Model

1.1 Set-up

Our model is built on Acemoglu and Autor (2011) (AA hereafter). Before analyzing workers' labor supply decisions, let us describe firms' labor demand for each type of tasks. Each firm employs a continuum of tasks, indexed by $z \in [0,1]$. Output of industry j requires possibly all task inputs, which for simplicity is described by the following production function:

$$y_j = \int_0^1 \beta_j(z) \ln y(z)\, dz. \tag{A-1}$$

The importance of task z in the production of j is captured by a continuous measure of weights, $\beta_j(z)$. Consider two industries, j and j', if $\beta_{j'}(z) > \beta_j(z)$, task z is used more intensively in the production of industry-j goods. To preserve the constant-returns-to-scale (CRS) property of the industry's production function, we assume that $\int_0^1 \beta_j(z)\, dz = 1$. Each task z combines skills (S) and brawn (B) inputs linearly as follows

$$y(z) = B(z) + a(z) S(z). \tag{A-2}$$

Skills and brawn are assumed to be perfectly substitutable. Which one is used to produce task z depends on the relative productivity of skills ($a(z)$) in delivering task z.

Now let us make two ranking assumptions. First, we rank tasks as follows:

Assumption 1:
$a(z)$ is continuously differentiable and strictly increasing in z.

In other words, skill inputs are more effective in delivering a high-z task. Second, we rank industries such that an industry with a higher j requires on "average" more skill inputs, as follows:

Assumption 2:
Industries are ranked in such a way so that $\int_0^k \beta_{j'}(z)\, dz > \int_0^k \beta_j(z)\, dz$ 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 $\frac{d\beta_{j'}(z)}{dz} \geq \frac{d\beta_j(z)}{dz}$ for all $z < [0,1]$ if $j > j'$. In that case, the weights, $\beta_j(z)$ is increasing in z faster than that in $\beta_j'(z)$, or high-z tasks are becoming increasingly more important.

Following AA, we derive the following proposition regarding the use of skills and brawn tasks.

Proposition A1 *There exists a threshold z_j^* for industry j such that all firms within the industry will use brawn inputs for all tasks $z \leq z_j^*$ and skill inputs for all tasks $z > z_j^*$.*
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 z_j^*. One unit of $y\left(z_j^*\right)$ can be done at the same cost by using brawn only, which cost w_B per unit, or skills only, which cost $\frac{w_S}{a(z^*)}$ per unit. Given Assumption 1, $\frac{w_S}{a(z)} < w_B$ for all $z > z_j^*$. In other words, it is strictly less costly to produce any tasks with $z > z_j^*$ using skills only rather than brawn only or a mix of the two. ■

1.2 The Law of One Price of Skills

Owners of skills and brawn are free to switch between tasks and industries. Free labor mobility implies no wage arbitrage. The resulting law of one price of skills implies

$$\begin{aligned} w_B &= p_j(z) \text{ for all } z \leq z_j^* \text{ and all } j; \\ w_S &= p_j(z)\, a(z) \text{ for all } z > z_j^* \text{ and all } j, \end{aligned}$$

where $p_j(z)$ is the price of task z used in industry j. In other words, given constant w_B, w_S, and $a(z)$, $p_j(z)$ will adjust in such a way to make sure that the above equations will hold.

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

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

where TVC stands for total variable cost.

Thus, for any two tasks that use brawn inputs, the following equality needs to hold:

$$\frac{p_j(z)\, B_j(z)}{\beta_j(z)} = \frac{p_j(z)\, B_j(z')}{\beta_j(z')}.$$

Constant w_B and w_S across tasks imply

$$\frac{B_j(z)}{\beta_j(z)} = \frac{B_j(z')}{\beta_j(z')}.$$

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

$$\frac{p_j(z)\, \alpha_S(z)\, S_j(z)}{\beta_j(z)} = \frac{p_j(z')\, \alpha_S(z')\, S_j(z')}{\beta_j(z')} \Longrightarrow \frac{S_j(z)}{\beta_j(z)} = \frac{S_j(z')}{\beta_j(z')}.$$

Given a firm's total demand for brawn and skills (B_j and S_j), the demand for each type of inputs for task z is

$$\begin{aligned} B_j(z) &= \begin{cases} \frac{\beta_j(z) B_j}{\beta_j} & \text{for all } z \leq z_j^* \\ 0 & \text{otherwise} \end{cases} \\ S_j(z) &= \begin{cases} \frac{\beta_j(z) S_j}{1-\beta_j} & \text{for all } z > z_j^*, \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

where $\beta_j = \int_0^{z_j^*} \beta_j(z)\, dz$.

1.3 Labor Supply

Let us now turn to the labor supply side of the model. The economy is endowed with two types of workers: male and female. Let us denote the mass of male workers and female workers by M and F, respectively. Each worker is endowed with both skills 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, Rosenzweig, and Hassan, 2012).[1] In other words, female workers have a comparative advantage in skill-intensive tasks. More formally, let θ_l^s and θ_l^b be the skill and brawn endowment of gender-l worker, respectively. These assumptions about men's (m) and women's comparative advantages imply that

$$\frac{\theta_m^S}{\theta_m^B} > \frac{\theta_f^S}{\theta_f^B}. \tag{A-3}$$

As in AA, each worker has 1 unit of time and has to decide how to allocate the time used to supply brawn or skills. The time budget constraints for each female and male workers are

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

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

Both female and male workers choose how much skill and brawn to supply, respectively, making the following wages:

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

where w_B and w_S are the wage rates for 1 unit of brawn and skills, respectively. Thus, the supplies of skills and brawn in the aggregate economy are endogenous.

As we have shown above, the wage rates for each unit of skill and brawn are the same regardless of which task or industry it is employed. All men 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

[1] 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.

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

Given assumption (A-3), 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 A1 *In equilibrium with no wage arbitrage, all female workers choose to supply skills, while all male workers choose to supply brawn.*

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. The inequality $w_S\theta_f^S \leq w_B\theta_f^B$ implies that all female workers will choose to supply brawn. Given assumption (A-3), $\frac{\theta_m^S}{\theta_m^B} \leq \frac{w_B}{w_S}$, the inequality $w_S\theta_m^S \leq w_B\theta_m^B$ implies that all males will choose to supply brawn as well. Zero supply of skills in the economy cannot be consistent with both w_B and w_S being positive in equilibrium and the fact that there will always be demand for skills according to Proposition A1. Thus, by contradiction, $\frac{\theta_f^S}{\theta_f^B}$ has to be weakly larger than $\frac{w_B}{w_S}$. 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 will also supply skills only. Zero supply of brawn services cannot be sustained in equilibrium, which is inconsistent to what we have proved in Proposition A1. Thus, $\frac{w_B}{w_S}$ has to be weakly larger than $\frac{\theta_m^S}{\theta_m^B}$. ■

This lemma implies a one-to-one mapping between female labor and skill supply, as well as male labor and brawn supply. Specifically, aggregating individuals' skill supplies in the economy gives $S = \theta_f^S F$ and that for brawn as $B = \theta_f^S M$.

Given no other intrinsic difference between workers beside gender, all female workers supply skills and get the same wage rate:

$$w_f = w_S\theta_f^S,$$

while all male workers supply brawn and get

$$w_m = w_B\theta_m^B.$$

1.4 Firm Equilibrium

Consider an unbiased firm that assign the two types of labor inputs to different tasks based on their task-specific labor productivities according to (A-2). According to Proposition A1, for all tasks $z \geq z_j^*$, only skill inputs will be used in industry j, while for all tasks $z < z_j^*$, only brawn inputs will be used. A combination of that proposition and the lemma in the previous section implies the following corollary.

Corollary A1 *Only female workers will be hired to do tasks $z \geq z_j^*$; while only male workers will be hired to do tasks $z < z_j^*$.*

We can thus rewrite the production function (A-1) for an unbiased firm in industry j as

$$y_j = \varphi_i \widetilde{\mu}_j S^{\beta_j} B^{1-\beta_j} \tag{A-4}$$

where φ_i is firm i's TFP; $\widetilde{\mu}_j = \exp \int_{z_j^*}^1 \beta(z) \log a(z)\, dz$; and $\beta_j = \int_{z_j^*}^1 \beta_j(z)\, dz$.

Since all skills are supplied by women while all brawn inputs are supplied by men, the production function can be re-written as

$$y_j = \varphi_i \mu_j f^{\beta_j} m^{1-\beta_j} \tag{A-5}$$

where $\mu_j = \left(\theta_f^S\right)^{\beta_j} \left(\theta_m^B\right)^{1-\beta_j} \widetilde{\mu}_j$.

2 Statistical Discrimination

Now let us study the behavior of firms with statistical discrimination. A biased firm perceives a lower productivity of female workers compared to their true levels. Specifically, it thinks that if a female worker supplies an input (either skill or brawn), her productivity is a fraction $\lambda \in (0, \infty)$ of the true productivity. A firm with $\lambda = 1$ is completely neutral to female workers. $\lambda < 1$ indicates an increasingly more negative view toward women while $\lambda > 1$ indicates a more favorable view, relative to the firm's view toward male workers.

The firm will still employ women for the very skill-intensive tasks because of their comparative advantage, but it will use more men for intermediate skilled tasks that should be (optimally) done by women.

We have the following proposition for biased firms, which complements Proposition A1:

Proposition A2 *There exists a firm-specific threshold $z_j^*(\lambda)$ for industry j such that it will use brawn inputs for all tasks $z \leq z_j^*(\lambda)$ and skill inputs for all tasks $z > z_j^*(\lambda)$. $\frac{\partial z_j^*(\gamma)}{\partial \lambda} < 0$.*

Proof. Again, the formal proof of this lemma can be found in Acemoglu and Zilibotti (2001). Similar to the previous proof, the task cutoff $z_j^*(\lambda)$, above which all tasks are done by skill inputs, is determined by the indifference condition: $w_B = \frac{w_S}{\lambda a(z^*)}$. Given that $a(z)$ is increasing in z (Assumption 1), $\frac{w_S}{\lambda a(z)} < w_B$ for all $z > z_j^*(\lambda)$. It is strictly less costly to produce any tasks with $z > z_j^*(\lambda)$ using skills only rather than brawn only or a mix of the two. Moreover, since $a(z)$ is increasing in z, a lower λ (a stronger bias) implies a higher $z_j^*(\lambda)$. ■

We can then express the production function of a biased firm as

$$y_j(\lambda) = \varphi_i \mu_j(\lambda) f^{\beta_j(\lambda)} m^{1-\beta_j(\lambda)}, \tag{A-6}$$

where $\mu_j(\lambda) = \left(\theta_f^S\right)^{\beta_j(\lambda)} \left(\theta_m^B\right)^{1-\beta_j(\lambda)} \widetilde{\mu}_j$ and $\beta_j(\lambda)$ is decreasing strictly in λ. Thus, even when we assume that there is no taste-based discrimination against women (i.e., $\gamma = 0$ for all firms), firm heterogeneity in $\beta_j(\lambda)$ would give us heterogeneous female-to-male labor shares across firms. By solving the firm's profit maximization problem, we obtain the female-to-male ratio as

$$\frac{f}{m} = \frac{\beta_j(\lambda)}{1 - \beta_j(\lambda)} \frac{w_m}{w_f},$$

which is decreasing in λ for a given β_j.

3 Proof of Proposition 1

A firm's maximization problem is

$$\max_{f,m} \pi^e(\varphi, \gamma) = \max_{f,m} \{R - w_f (1+\gamma) f - w_m m - \phi\},$$

First order conditions yield

$$\begin{aligned} \beta\eta R &= w_f(1+\gamma)f; \\ (1-\beta)\eta R &= w_m m. \end{aligned} \tag{A-7}$$

Combining these two equations yields

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

It can be shown that a firm's female-to-male ratio is decreasing in γ,

$$\frac{\partial}{\partial \gamma}\left(\frac{f}{m}\right) = -\frac{\beta}{(1-\beta)(1+\gamma)^2} \frac{w_m}{w_f} < 0,$$

and such relationship is stronger for higher β,

$$\frac{\partial^2}{\partial \gamma \partial \beta}\left(\frac{f}{m}\right) = -\frac{1}{(1-\beta)^2(1+\gamma)^2} \frac{w_m}{w_f} < 0.$$

4 Proof of Proposition 2

Plugging $R = A^{1-\eta}(y)^\eta$ into $(A-7)$ yields the following relationship between y and f:

$$\beta\eta A^{1-\eta} y^\eta = w_f(1+\gamma)f. \tag{A-8}$$

Rewrite the production function as $y = \varphi\left(\frac{f}{m}\right)^{\beta-1} f$. Since $\frac{f}{m} = \frac{\beta}{(1-\beta)(1+\gamma)} \frac{w_m}{w_f}$, we have

$$y = \varphi \left(\frac{\beta}{(1-\beta)(1+\gamma)} \frac{w_m}{w_f} \right)^{\beta-1} f. \tag{A-9}$$

From $(A-8)$ and $(A-9)$, we can solve for y and f. Substituting y into the revenue function yields the expression for R. Thus, the output and revenue can be written as

$$y(\varphi,\gamma) = A \left[\frac{\eta\varphi D}{c(\gamma)} \right]^{\sigma}; \tag{A-10}$$

$$R(\varphi,\gamma) = A \left[\frac{\eta\varphi D}{c(\gamma)} \right]^{\sigma-1},$$

where $D = \beta^{\beta}(1-\beta)^{1-\beta}$ and $c(\gamma) = w_f^{\beta}(1+\gamma)^{\beta} w_m^{1-\beta}$. Since $c(\gamma) = (w_f(1+\gamma))^{\beta} w_m^{1-\beta}$ is increasing in γ, it is obvious that a firm's output and revenue are both decreasing in γ.

Note that the *actual* profit function is different from the *perceived* profit function. Substituting the optimal labor f^* and m^* into the *actual* profit function (equation (3) in the main text), we have

$$\pi(\varphi,\gamma) = A(\eta D)^{\sigma-1} \left[\frac{\varphi}{c(\gamma)} \right]^{\sigma-1} \left[1 - \eta \left(1 - \frac{\gamma\beta}{1+\gamma} \right) \right] - \phi. \tag{A-11}$$

It can be shown that

$$\begin{aligned} \frac{\partial \pi(\varphi,\gamma)}{\partial\gamma} &\propto (1+\gamma)^{\beta(1-\sigma)} \left[\beta(1-\sigma)(1+\gamma)^{-1} + \eta\beta(1+\gamma)^{-1} \right] \\ &\propto -\beta(\sigma-1)(1+\gamma)^{-1} < 0. \end{aligned}$$

5 Proof of Proposition 3

This section provides the proofs of Proposition 3 and the aggregate TFP loss due to discrimination. Most of the results are drawn from Hsieh and Klenow (2009).

Substituting $(A-10)$ into the firm demand function (equation (1) in the main text), $y_{ij} = A_j p_{ij}^{-\sigma}$, we get the price of firm i in industry j

$$p_{ij} = \frac{\sigma}{\sigma-1} \frac{w_f^{\beta_j}(1+\gamma_i)^{\beta_j} w_m^{1-\beta_j}}{\varphi_{ij}\beta_j^{\beta_j}(1-\beta_j)^{1-\beta_j}}.$$

We can now compute revenue TFP ($TFPR$) as

$$TFPR_{ij} = p_{ij}\varphi_{ij} = \frac{\sigma}{\sigma-1} \frac{w_f^{\beta_j}(1+\gamma_{ij})^{\beta_j} w_m^{1-\beta_j}}{\beta_j^{\beta_j}(1-\beta_j)^{1-\beta_j}} \propto (1+\gamma_{ij})^{\beta_j}.$$

In the absence of discrimination, $TFPR_{ij}$ only depends on industry-level parameters and should be equalized across firms within each industry.

Define industry level productivity as $TFP_j = Y_j / \left(F^{\beta_j} M_j^{1-\beta_j} \right)$, where Y_j is the industry's output, and F_j and M_j are its female and male labor inputs. Hsieh and Klenow (2009) show that

$$TFP_j = \left[\sum_{i=1}^{N_j} \left(\varphi_{ij} \frac{\overline{TFPR}_j}{TFPR_{ij}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}},$$

where $\overline{TFPR}_j$ is a weighted average of $TFPR_{ij}$, and N_j is the number of differentiated products. When there is no discrimination, $\frac{\overline{TFPR}_j}{TFPR_{ij}} = 1$. Therefore, the efficient industry TFP should be $TFP_j^e = \left[\sum_{i=1}^{N_j} \varphi_{ij}{}^{\sigma-1} \right]^{\frac{1}{\sigma-1}}$.

In the Hsieh-Klenow framework, the dispersion of $TFPR_{ij}$ is an outcome of distortions. Based on the assumptions that φ_{ij} and $1+\gamma_{ij}$ are independent and follow normal distribution, we have the following decomposition of the industry TFP,

$$\log TFP_j = \log TFP_j^e - \frac{\sigma \beta_j}{2} var\left(TFPR_{ij}\right) = \log TFP_j^e - \frac{\sigma \beta_j}{2} \nu_{j.}$$

Economy wide TFP is simply the Cobb-Douglas aggregate of the industry level TFP.

6 Proof of Proposition 4

The marginal effect of a smaller bias among observed FIEs against female workers can be analytically expressed as

$$\begin{aligned} \frac{\partial}{\partial(-\overline{z})} E\left[f/m|\overline{z},\psi\right] &= \frac{\beta}{1-\beta} \frac{w_m}{w_f} \frac{\partial}{\partial(-\overline{z})} \left\{ E\left[\frac{1}{1+\gamma} |\overline{z},\psi \right] \right\} \\ &= \frac{\beta}{1-\beta} \frac{w_m}{w_f} \frac{\partial}{\partial(-\overline{z})} E\left\{ \left[\exp\left[-\log\left(1+\gamma\right)\right] |\overline{z},\psi \right] \right\}. \end{aligned}$$

Given the assumption that $(1+\gamma)$ is log-normally distributed, the right hand side of the above equation can be expressed as

$$\begin{aligned}
\frac{\partial}{\partial(-\overline{z})}E\left[f/m|\overline{z},\psi\right] &= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial\overline{z}}\left\{\exp\left(E\left[\log\left(1+\gamma\right)|\overline{z},\psi\right]+\frac{1}{2}Var\left[\log\left(1+\gamma\right)|\overline{z},\psi\right]\right)\right\} \quad \text{(A-12)}\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial\overline{z}}\left[\exp\left(\psi'+\frac{1}{2}v'\right)\right]\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial}{\partial\overline{z}}\left(\psi'+\frac{1}{2}v'\right)\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial}{\partial\overline{z}}\left(\underbrace{\delta\overline{z}+(1-\delta)\,\psi}_{\psi'}\right)\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\delta>0.
\end{aligned}$$

Similarly, we can derive the marginal effect of a reduction in ω^* (i.e., the FIEs' uncertainty in the belief about female labor cost) as

$$\begin{aligned}
\frac{\partial}{\partial(-\omega^*)}E\left[f/m|\overline{z},\psi\right] &= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial(-\omega^*)}\left\{E\left[\frac{1}{1+\gamma}|\overline{z},\psi\right]\right\} \quad \text{(A-13)}\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial(-\omega^*)}E\left\{\left[\exp\left[-\log\left(1+\gamma\right)\right]|\overline{z},\psi\right]\right\}\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial\omega^*}\left[\exp\left(\psi'+\frac{1}{2}v'\right)\right]\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial}{\partial\omega^*}\left(\psi'+\frac{1}{2}v'\right)\\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial}{\partial\omega^*}\left(\frac{1}{2}v'\right)\\
&= \frac{1}{2}\frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial}{\partial\omega^*}\left(\frac{\omega^* v}{\omega^*+nv}\right)\\
&= \frac{1}{2}\frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\frac{nv^2}{(\omega^*+nv)^2}>0
\end{aligned}$$

Using the expression in equation $(A-12)$, we can derive the second derivative of $\frac{\partial}{\partial(-\overline{z})}E\left[f/m|\overline{z},\psi\right]$, with respect to the number of FIEs observed, as

$$
\begin{aligned}
\frac{\partial}{\partial n}\frac{\partial}{\partial\left(-\overline{z}\right)}E\left[f/m|\overline{z},\psi\right] &= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\frac{\partial}{\partial n}\left[\exp\left(\psi'+\frac{1}{2}v'\right)\delta\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\left[\delta\frac{\partial}{\partial n}\left[\exp\left(\psi'+\frac{1}{2}v'\right)\right]+\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial\delta}{\partial n}\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\left[\delta\exp\left(\psi'+\frac{1}{2}v'\right)\left(\frac{\partial\psi'}{\partial n}+\frac{1}{2}\frac{\partial v'}{\partial n}\right)+\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial\delta}{\partial n}\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\left[\delta\exp\left(\psi'+\frac{1}{2}v'\right)\left(\left(\overline{z}-\psi\right)\frac{\partial\delta}{\partial n}+\frac{1}{2}\frac{\partial v'}{\partial n}\right)+\exp\left(\psi'+\frac{1}{2}v'\right)\frac{\partial\delta}{\partial n}\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\left[\left(1+\delta\left(\overline{z}-\psi\right)\right)\frac{\partial\delta}{\partial n}+\frac{\delta}{2}\frac{\partial v'}{\partial n}\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\left[\left(1+\delta\left(\overline{z}-\psi\right)\right)\frac{\partial\left(\frac{nv}{\omega^*+nv}\right)}{\partial n}+\frac{\delta\left(\frac{\omega^* v}{\omega^*+nv}\right)}{2}\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\left[\left(1+\delta\left(\overline{z}-\psi\right)\right)\left[\frac{\omega^* v}{\left(\omega^*+nv\right)^2}\right]-\frac{\delta}{2}\left(\frac{\omega^* v^2}{\left(\omega^*+nv\right)^2}\right)\right] \\
&= \frac{\beta}{1-\beta}\frac{w_m}{w_f}\exp\left(\psi'+\frac{1}{2}v'\right)\left(\frac{\omega^* v}{\left(\omega^*+nv\right)^2}\right)\left[\left(1+\delta\left(\overline{z}-\psi-\frac{v}{2}\right)\right)\right]
\end{aligned}
$$

$$
\begin{aligned}
\delta &= \frac{nv}{\omega^*+nv} \\
&= \frac{nv}{\left(\nu^*+\nu_w\right)+nv}
\end{aligned}
$$

$$
\overline{z} > \left(\psi+\frac{v}{2}-1-\frac{\nu^*+\nu_w}{nv}\right)
$$

References

[1] Acemoglu, Daron, and Fabrizio Zilibotti (2001) "Productivity Differences" *Quarterly Journal of Economics*, 116(2), pp. 563-606.