Journal of International Economics 133 (2021) 103518

Contents lists available at ScienceDirect

Journal of International Economics

journal homepage: www.elsevier.com/locate/jie

Full Length Articles

Do multinationals transfer culture? Evidence on female employment in China☆

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ARTICLE INFO

Article history:
Received 28 April 2020
Received in revised form 16 July 2021
Accepted 19 July 2021
Available online 29 July 2021

Repository data link: https://nam03.safelinks.protection.outlook.com/?

JEL classification:
F11
F21
J16
L22
O47

Keywords:
Cultural spillovers
Gender inequality
FDI
Misallocation
China

ABSTRACT

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

1. Introduction

Multinational firms are an important vehicle for the cross-country dissemination of ideas, capital, and technology.[1] Social scientists have long studied how multinationals can shape host countries' social norms and values, and thus contribute to a potential global cultural convergence, in addition to the global economic convergence.[2] However, economics research on the cultural effect

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

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

[2] Numerous discussions of cultural homogenization and clashes have been published, including Thomas Friedman's (1999) famous work that claims that "No two countries with McDonald's have ever gone to war since each got its McDonald's," and the classic "The Clash of Civilizations and the Remaking of World Order" by Samuel Huntington (1996).

https://doi.org/10.1016/j.jinteco.2021.103518

of foreign direct investment (FDI) is limited, partly because of the challenges in quantifying culture, let alone identifying its dissemination.

This study contributes to the debate on the cultural effects of economic globalization by examining 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 transfer within multinational firms and cultural spillovers to domestic firms. Studying China's gender inequality is of interest, first because of the country's deep cultural links to Confucianism, which advocates the subservience of women to men. Second, income and gender inequalities have increased rapidly in China since its government's implementation of market reforms in the late 1970s (Cai et al., 2008).[3]

We show that FDI may have an unexpected productivity effect due to the dissemination of culture by multinational firms. By inferring firms' attitudes toward women from their female labor share (i.e., share of women in a firm's employment), we find that foreign affiliates from countries with a more gender-equal culture tend to employ proportionally more women and appoint more female managers. Specifically, a one standard deviation decrease in gender inequality index of the country of origin (equivalent to reducing Malaysia's gender inequality to that of Germany, based on the United Nations Development Program's (UNDP) gender inequality index) is associated with an average increase of 1.9 percentage points in female labor share in its affiliates, after controlling for four-digit industry and province fixed effects. These results remain robust when we control for various firms' characteristics, including their skill levels and other technology measures.

Perhaps more surprisingly, multinational firms appear to influence domestic firms' attitudes toward female workers, as we find that domestic firms' female labor shares and their likelihood of having female managers both increase with the prevalence of foreign affiliates in the same industry or city. These correlations are robust to the control of the degree of market competition, 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 the output share of foreign firms in the same city (industry) is associated with an average increase of 1.7 (0.7) percentage points in the female labor share among domestic firms. These cultural spillovers from foreign firms are greater if the source of FDI is from a more gender-equal country, suggesting that these changes in the female labor share in domestic firms are not solely driven by changing economic conditions in the labor or goods markets.

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

We incorporate firms' taste-based discrimination into our model, à la Becker (1957). Specifically, each firm draws its own subjective variable cost of female workers 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. The biased perceived costs of female workers, compared with the objective benchmark, cause firms to employ fewer female workers, thereby reducing their profits. Indeed, we find in our data a positive correlation between firms' time-varying profits and their 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 through which domestic firms update their (biased) beliefs about the cost of female workers in the direction of the objective benchmark, similar to the cultural transmission model of Bisin and Verdier (2000, 2011) and Fernandez (2013). In our model, a domestic firm updates its prior belief when its belief differs from the average belief among the foreign firms it interacts with. The extent of belief updating is greater when the firm interacts with more foreign firms. The predictions of our model in terms of 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 from an alternative model with statistical discrimination, as in Phelps (1972) and Arrow (1973).

In the final part of the paper, we quantify the aggregate productivity loss due to gender discrimination and the gain associated with the cultural effect of FDI, using the average revenue product (ARP) approach proposed by Hsieh and Klenow (2009). After fully eliminating gender discrimination by setting the female-to-male labor ratios of all firms to the benchmark based on the corresponding U.S. industry, we find that China's aggregate manufacturing total factor productivity (TFP) increases by about 5%, compared with a 33% TFP gain when removing all capital distortions. The cultural effect of FDI is also estimated to reduce the dispersion of firms' female-to-male employment ratios within industries, contributing around 1% of the increase in China's aggregate manufacturing TFP.

[3] According to a survey of more than 3000 women conducted in 2009 by the Center for Women's Law and Legal Services at Peking University, more than 20% said their employers cut salaries for women who become pregnant and 11.2% lost their jobs after having a baby. More than one third of the women surveyed believed that male employees have more promotion opportunities. Gender inequality in China was significantly reduced under the egalitarian policies spearheaded by Mao. For example, in the 1950s women won the right to own property and land, and to vote. They gained the freedom to marry and divorce for the first time in Chinese history after the marriage law passed in 1950. Female participation in the labor force also soared, with more women becoming government leaders and role models workers in state-owned enterprises.

This paper contributes to several areas of the social science literature. First of all, it adds to a large body of work in sociology and anthropology that examines the relation between globalization and culture (e.g., Hofstede, 1980; Pieterse, 2003; Hopper, 2007),[4] by offering empirical support for the "cultural convergence" hypothesis and related case studies.

This paper is also related to the economics literature on culture. Economists have identified systematic differences in social norms and beliefs across countries and have related them to various individuals' economic behaviors, such as saving, participation in the financial market, investment in education, and preferences for redistribution (Guiso et al., 2006; Fernandez, 2011), in addition to macroeconomic outcomes such as economic growth (Gorodnichenko and Roland, 2017) and the patterns of bilateral trade and FDI (Guiso et al., 2009). Other 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). Research specifically related to gender norms shows that progress has been slow, as prejudices against certain groups in society often have deep historical roots (e.g., Jayachandran, 2015). Such hypothesis has been empirically verified by Alesina et al. (2013), who show that the descendants of societies that practiced plough agriculture more intensively in the past have less equal gender norms today. Our study illustrates how economic globalization can in fact change gender norms in a society relatively quickly. Kodama et al. (2018) find that in Japan, the proportions of women in overall employment and in management are on average higher and that the gender wage gap is smaller in foreign affiliates than in domestic firms. Foreign affiliates also tend to implement women-friendly human resource policies. Choi and Greaney (2019) find that in Korea, foreign affiliates from more gender-equal countries have higher levels of female employment and are more likely to have a female CEO. Our paper further these studies that document the existence of culture transfer by theoretically and empirically examining the mechanism of cultural spillovers and the associated productivity gain.

As we focus on firms' revealed preferences for female workers, our study contributes to the extensive literature on gender discrimination (e.g., Altonji and Blank, 1999; Bertrand, 2011; Duflo, 2012). In his classic work, Becker (1957) hypothesizes that discriminatory firms will be driven out of business in the long run through market competition. Several studies have empirically verified Becker's hypothesis in the context of trade (Borjas and Ramey, 1995; Black and Brainerd, 2004; Juhn et al., 2014).[5] Research also attempts to quantify the cost of discrimination (Kawaguchi, 2007; Cavalcanti and Tavares, 2016; Hsieh et al., 2019). Hsieh et al. (2019) find that the improved talent allocation across gender and racial groups can explain about a quarter of the U.S. aggregate output growth per worker between 1960 and 2008.[6] Complementing their findings, we provide the first 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 the emerging literature on the relation between foreign affiliate outcomes and the characteristics of their countries of origin. Based on U.S. employer-employee matched data, Setzler and Tintelnot (2019) find that an expansion of FDI from high-income countries leads to more skilled workers employed and a higher wage premium in the local labor market. Hjort et al. (2020) show that changes in the minimum wages in FDI source countries can affect the wages of their foreign affiliates. Gong (2020) finds that U.S. state-level R&D tax credit policies are associated with technology transfer to and spillovers from the U.S. subsidiaries in China.

Finally, our paper contributes to the extensive literature about the effects of FDI on host countries. Studies on 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 can transfer culture from a firm's home country and shape social norms in its host country. Our findings suggest that the gradually closing gender gap in some developing countries could be partially attributed to gender cultural spillovers, a previously overlooked aspect of FDI in the literature.[7]

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

2. Model

To provide theoretical foundation for our empirical analysis and quantitative exercise, we introduce a multi-sector task-based model with firm heterogeneity in productivity, bias toward female workers, and learning within sectors or regions. We outline the key features and results of the model in the main text, leaving all technical details and proofs to the appendix.

[4] The social psychologist Hofstede (1980) demonstrates 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 the cultures of countries. They examine three paradigms: the "clash of civilizations", "McDonaldization," and "hybridization."

[5] Black and Brainerd (2004) find that increased 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, particularly among blue collar workers, as the intensive use of machines by new exporters replaces physically demanding tasks in which male workers have a comparative advantage.

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

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

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 preferences. Consumers consume goods based on a Cobb-Douglas utility function with constant expenditure shares θ_j over industries indexed by $j = \{1,2,\ldots,J\}$. 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.[8]

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 is higher than men, as assumed by Pitt et al. (2012).[9]

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. 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

Regarding the demand side of the labor market, while we can simply assume that industries vary in female labor intensity, as in Do et al. (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 more details).

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 a 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. For ease of notation, let us now suppress both firm and industry subscripts.

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 toward 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-normal distribution over the entire real line, with mean $\psi \geq 0$ and variance $\nu > 0$:

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

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

[9] 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.

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.[10] 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.[11] 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? Many examples illustrate why perceptions about certain groups in society are often shaped by simple rule-of-thumb decisions. For instance, Alesina et al. (2013) postulate that it takes a long time for agents to potentially realize the cost of their suboptimal choices due to prejudices.[12]

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

A firm's profit function is equal to 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[13]:

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

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:

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

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

All else being equal, a firm's female-to-male labor ratio is decreasing in γ, especially in 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 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 expect a firm from country c to have a higher average $\frac{f}{m}$ due to a lower expected γ. Let us summarize these results in the following proposition.

Proposition 1. *Firms from countries that hold a more biased view of female labor costs* (i.e., *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 of 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 provide 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 assumption 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 bias and their female labor share.

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

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

[12] 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.

[13] Note that a firm can also have a preference for 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).

2.2.3. Effects on firm profits

We now examine the effects of gender discrimination on firm and aggregate economic outcomes. Substituting the firm's privately optimal choice of female and male workers into its production and revenue functions yields the following firm output and revenue[14]:

$$y(\varphi,\gamma) = A\left[\frac{\eta\varphi D}{c(\gamma)}\right]^{\sigma}; \tag{6}$$

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

where $D = \beta^{\beta}(1-\beta)^{1-\beta}$ and $c(\gamma) = w_f^{\beta}(1+\gamma)^{\beta}w_m^{1-\beta}$. Since $c(\gamma)$ 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 both economic and social points 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

$$p(\varphi,\gamma) = \frac{c(\gamma)}{\varphi\eta D};$$

$$TFPR(\gamma) = p(\varphi,\gamma)\varphi = \frac{c(\gamma)}{\eta D}.$$

A higher γ, through increasing the variable cost of production, raises $p(\varphi,\gamma)$ and $TFPR(\gamma)$. Intuitively, a firm's biased view of female labor costs reduces its quantity supplied, thus raising its goods price. A higher TFPR may not imply a higher efficiency. On the contrary, 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 by 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, a firm's optimization will set its TFPR 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.[15] Finally, the economy's aggregate TFP, based on consumers' Cobb-Douglas utility function, can be expressed as $TFP{=}_{j=1}^{J}TFP_j^{\theta_j}$.

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

Proof: See the appendix.

[14] Note 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 value.

[15] In Section 5, we will consider output and capital distortions, and allow correlations between all distortions in the computation of the productivity loss.

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 loss due to gender bias, 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). In terms of competition, the entry of foreign invested enterprises (FIEs) into a market may drive up input costs but lower final 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 toward 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 of 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 change their employment decisions. To illustrate the main theoretical points, we consider only one foreign country of origin.[16]

Consider a domestic firm that observes imperfectly FIEs' γ with noise in the same market (city or industry).[17] 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 on average than domestic firms. 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. For the ease of 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 $\bar{z}'s$ inferred from n neighbors, the firm updates its prior according to Bayes' rule. The posterior belief is normally distributed with the following mean ψ'[18]:

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

where δ is the weight the firm puts on the observed (sample) mean $\bar{z} = \frac{1}{n}\sum_{l=1}^{n} z_l$, based on the 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:

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

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 $\bar{z} < \psi$ or not. If the observed FIEs hold a less biased view toward women than the domestic firm itself (i.e., $\bar{z} < \psi$), a greater number of FIEs induces a larger extent of belief updating toward 0; whereas FIEs' more biased views observed by the firm (i.e., $\bar{z} > \psi$) will lead to belief updating away from 0, especially when more FIEs are observed. The general theoretical results are summarized in the following proposition.

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

[17] 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-to-male labor ratio, which the firm can then infer the subjective labor cost of an observed FIE as $1+\gamma = \frac{m}{f}\frac{\beta}{1-\beta}\frac{w_m}{w_f}$.

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

Proposition 4. *The average domestic firms' female labor share is decreasing in the observed average FIEs' belief in the cost of female workers* ($\bar{z}$)*, and 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

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

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 larger variance.

In summary, 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 toward 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 obtained from the annual industrial firm surveys of China for the 2004–2007 period. The surveys, conducted by the country's National Bureau of Statistics (NBS), cover all state-owned firms and all non-state-owned firms that have sales over RMB 5 million (about USD 0.7 million at the 2007 exchange rate).[19] Basic firm balance sheet information, such as output, value added, fixed assets, exports, employment, and industry code and ownership type (foreign or domestic in particular) are available. Despite the sampling threshold, the data are representative. Compared with the 2004 economic census, the aggregate data based on our firm data accounted for 91%, 71%, 97%, and 91% of China's total industrial output, employment, exports, and fixed assets, respectively. To construct a panel data set, we use unique firm ID and contact information to identify identical firms across the years.[20] We compute firms' real capital stock and TFP, following the method proposed by Brandt et al. (2012).

We use the following variables to construct a firm's female labor share, which is the main variable of interest in our regression analysis:

1. For 2004, we have information on firm employment by gender and education level. A worker is considered skilled if s/he has a high school education or above. About 45% of all employees in our data are considered skilled in 2004.[21]
2. For 2005, 2006, and 2007, we have information on employment by gender but not by education level.

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 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. Due to this limitation, we assess gender bias based on the varying female labor share across firms.[22] A firm's foreign ownership status is identified based on its registration type. We obtain information on FIEs' countries of origin from *Foreign Invested Firms Surveys* conducted by China's Ministry of Commerce

[19] We do not have firms in the service sector in our data. During our sample period, FDI in the service sector was lower than in the manufacturing sector. According to China Statistical Yearbook 2005 (Tables 18–17), in 2004, only 26% of FDI inflows went to the service sector.

[20] A firm's ID may change over time, possibly due to restructuring or mergers and acquisitions. To resolve this data issue, we complement a firm's ID using its name, sector, and address to identify the same firm over time.

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

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

(MOC). We then merge the country-of-origin data with the NBS firm survey data, using firms' names and other contact information.

3.2. Identifying managers' gender

More prejudices against women often arise at the top levels of a firm (Bertrand and Hallock, 2001). This is often referred to as the "glass ceiling" effect, which prevents women from getting promoted to senior-level management positions (Nevill et al., 1990). Do cultural spillovers also affect firms' appointment of female managers? We can only address this question by obtaining information on the gender of the manager of each firm. Unfortunately, the NBS industrial firm survey dataset only provides the names of the legal representatives, but not their gender.[23] To overcome this data limitation, we apply a new 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.[24] We use a 20% random sample of China's 1% population census 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[25]:

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

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 10 characters with the highest (lowest) probability of being female. For the top 10 highest female characters, the probability that any of these 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 UNDP in 2011.[26] 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 bias. This covers three aspects of a country's gender inequality: reproductive health, empowerment, and labor market participation. A higher GII indicates greater gender inequality. As Table A2 in the appendix shows, the five countries with the lowest GII are all in Europe. In contrast, the five countries with the highest GII are located in the Middle East and Africa. A country's GII is obviously correlated with its income level, but there are rich countries with a very high GII (e.g., Saudi Arabia) and poor countries with a low GII (e.g., the Philippines). In the regression analysis below, we control for countries' income level. The GII data are not available for the three ethnic Chinese FDI sources of Hong Kong, Macau, and Taiwan, so we exclude firms whose majority of shares are owned by investors from these economies.[27]

3.4. Industry-level data

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

The key industry-level measure is female labor intensity, obtained from Do et al. (2016). The data are originally taken from a publication by the U.S. Bureau of Labor Statistics (BLS) entitled "Women in the Labor Force: A Databook." This contains information on total employment and the proportion of female employees in each four-digit industry (262 categories) defined by the US Census's Current Population Survey, covering both manufacturing and non-manufacturing sectors.[28] For each industry, we first take the average of the female labor share across the sample years from 2004 to 2009. We then retain 77 manufacturing or mining sectors, and match each of them to a specific NAICS six-digit code (511 categories), using the concordance table provided on the US Census website. Finally, we match the NAICS six-digit codes to unique Chinese four-digit industry codes (CIC codes), using a concordance table constructed by Ma et al. (2014). We then aggregate these measures to the CIC three-digit level (166 categories).[29]

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

[24] A Chinese name is typically written with the last name first, followed by the 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 gender. Thus, we only focus on the last character of a Chinese name.

[25] We restrict our sample to people aged 35 to 65 in 2005.

[26] These reports have been published since 2008. We choose 2011 to maximize country coverage.

[27] Given that most of the people in these three economies are ethinic Chinese, who may be more able to successfully adapt to the local culture, measures of their gender norms, even when available, may not be reflected in their employment practices in China. In addition, whether we can treat ethnic Chinese investments as FDI is up for debate. In any case, this data limitation forces us to drop FIEs with major investors from ethnic Chinese economies, which account for about 48% of the FIEs in the 2004 cross section.

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

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

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, textile, footwear, and leather. Those with the lowest share are cement and steel, which are likely to involve more 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 female labor share is 0.41. Among the subsample of Chinese domestic firms (about 78% of the firm-year observations), the mean is 0.39, compared with 0.48 for FIEs (excluding Hong Kong, Macau, and Taiwan's FIEs). FIEs also appear to be more likely to appoint women as managers. Of all firms for which the name of the manager (legal representative) can be identified, the proportion of firms that have a female manager is 0.25, compared with 0.24 for domestic firms and 0.26 for FIEs. Table 1 also reports the means and standard deviations for all of the variables used in the regressions at the firm, country, industry and city levels.

Fig. 1 plots the kernel density of female labor share for both domestic firms and FIEs in 2004, showing that a significantly higher number of FIEs have a higher female labor share. To partially address the concern that FIEs are distributed unevenly across industries, due to differences in comparative advantages for instance, Fig. 2 plots the kernel density of firms' female labor share after demeaning them from their corresponding four-digit industry averages. Fig. 2 confirms that the different distributions of female labor share between domestic firms and FIEs are not driven by the varying prevalence of FIEs across industries.[30]

4. Empirical evidence

4.1. Cultural transfer within multinational firm boundaries

We first empirically examine Proposition 1, which considers the cultural transfer 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:

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

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 firm i 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 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 gender norms of the multinationals' countries of origin.

The regressor $\mathbf{X}_{ic}$ is a vector of firm-level variables used to control for other determinants of female employment that have been proposed in the literature. To the extent that investments in capital, technology, and automation in production reduce the demand for physically demanding tasks (Juhn et al., 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 lower average wage of female workers resulting from gender bias in the labor market, and (log) output to take into account any firm-level scale effect on female employment.[31]

FIEs may adapt to the local business culture over time. In their initial years of operation in China, they may bring aspects of their home cultures to the host country. Such cultural transfer may, however, dissipate over time if the affiliate begins to be assimilated into the local culture and acts more like a domestic firm. We control for this potential assimilation effect by including the FIE's log(age) as a regressor. Finally, we include province and four-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 share, such as an industry's female comparative advantage. ε_{ic} is the error term.

The regression results reported in Table 2 strongly support Proposition 1. By controlling for province and four-digit industry fixed effects but without any other firm covariates, Column 1 shows a negative and fairly significant (at the 5% level) correlation between the *GII* of the multinationals' home countries and their affiliate's female labor share 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 points increase in the female labor share

[30] 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 control for a host of firm-level technology measures to deal with this potential within-industry variation.

[31] 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. Our regression results confirm this.

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	1046
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
Herfindahl 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).
See definitions in Table A3 in the appendix.

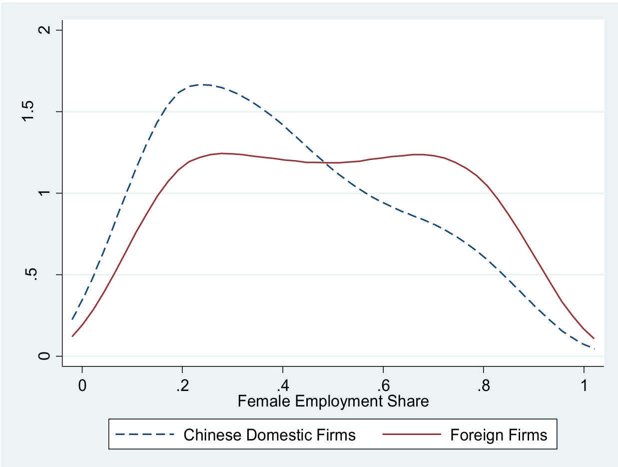

Fig. 1. Distribution of Firms' female labor share (2004). (Source: NBS annual survey of industrial firms (2004) and authors' calculation.)

in that country's affiliates in China. Moreover, we do not find any 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 share. In other words, our results indicate that among FIEs in China, technology does not appear to complement firms' female employment. Older FIEs hire proportionately more women on average, rejecting the assimilation hypothesis in this context.

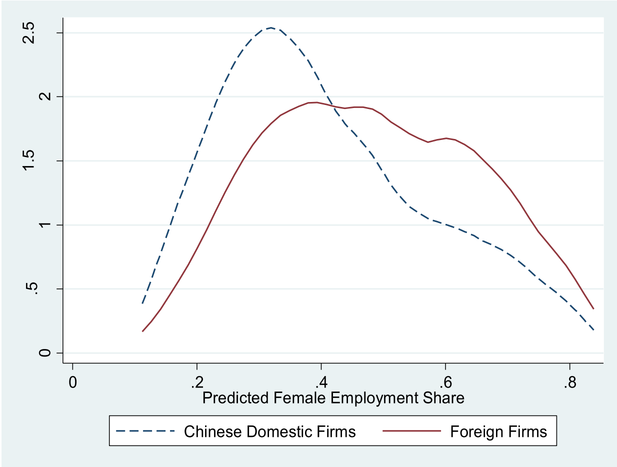

Fig. 2. Distribution of Firms' female labor share (2004) (controlling for 4-digit Industry Fixed Effects). (Source: NBS annual survey of industrial firms (2004) and authors' calculation.)

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 (−2.12)**	−0.099 (−4.32)***	−0.122 (−1.75)*	0.015 (0.26)
GII * Female comp. Advantage				−0.305 (−2.94)***
ln(GDP/pop)		0.003 (0.89)	0.005 (0.79)	0.001 (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	7884	10,693
Adj. R-sq	0.515	0.568	0.156	0.576

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.

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

In Column 4, we add an interaction term between an industry's female labor intensity, measured using the U.S. data as described in Section 3.4, and the *GII* of the FIE's source country. 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 1, which suggests that cultural transfer from multinationals is stronger in female labor-intensive industries. In summary, the results in Table 2 indicate that multinationals' cultural transfer is not a general feature of FDI, as the culture of the country of origin matters.

We examine the robustness of our gender culture measure in the 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 measure using a principle component analysis. In particular, we construct a composite 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 gender equality index of World Value Survey in 2005, based on 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 the 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.

It could be argued that FIEs employ more women than domestic firms because they intend to exploit the lower equilibrium wages of women, which can arise from the gender discrimination in labor market (Siegel et al., 2014). Another alternative hypothesis is that women are attracted to those locations where foreign firms are prevalent. Both possibilities imply 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 transfer 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 do not imply causality, they suggest that FIEs do not appear to be attracted to markets where female wages are lower or that they depress female wages.

4.2. Firms' female labor share and profits

We empirically examine Proposition 2 concerning the positive relationship between firms' profits and their female labor share. We regress a firm's profitability, defined as the ratio of profit to sales, on its female labor share, using 2004–2007 panel data.[32] Column 1 of Table 3 shows a positive and statistically significant correlation between these two variables. 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.[33] 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 technology 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.[34] The specification for estimating cultural spillovers is

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

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*.[35] $import_k$ and $Herf_k$ represent the import-to-output ratio and the Herfindahl index, respectively.[36] 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 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, which can occur if more FIEs appear in the market. To the extent that these measures capture the changes in the degree of market competition, any identified effect of FDI on firms' female labor share should be above and beyond the standard competition effect.[37]

As often emphasized in the FDI literature, domestic firms learn from FIEs in terms of product design, production technology, and foreign sales opportunities. These knowledge spillovers can be gender-biased. For example, technology upgrading can increase the demand for female labor (Juhn et al., 2014). To partially control for the technology-induced effect on employment, in the regressions we include various measures of technology, $\mathbf{X}_{ik}$, as 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 the regression results in Table 4 with markets defined as four-digit industries, and then report the results with markets defined as prefecture cities in Table 5. Based on the 2004 sample, Column 1 of Table 4 shows that domestic firms' female labor share increases 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, this cannot explain the negative correlation between the import-output ratio and domestic firms' female labor share across industries. In Column 2, we find that the probability of a domestic firm having a female manager is positively correlated

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

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

[34] China has 345 prefecture-level cities.

[35] We exclude invested firms from Hong Kong, Macau and Taiwan when measuring the output share of FIEs. The spillover effect is weaker but qualitatively similar when we include these firms. The estimation results are available upon request.

[36] The HS eight-digit product level import data come from Chinese Customs, which we further aggregate to the four-digit industry level.

[37] Note that it is difficult to quantitatively separate the competition effect from the cultural effect.

Table 3
Female labor share and profitability.

Sample:	(1) All Firms of 2004–2007 Panel	(2) 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

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

$FDI_{industry}$ 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.

with the output share of FIEs across industries.[38] In particular, when 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 an increase of 1.02 percentage points in the likelihood that a domestic firm appoints a female manager.

The positive cross-industry correlation between domestic firms' female labor share and FIEs' output share may simply reflect FIEs' self-selection into those industries that women have a comparative advantage. To address this concern, in Columns 3–7, we use the 2004–2007 panel data so that firm fixed effects can be included to explore a firm's potential response to a change in FIEs' prevalence in the same market. According to the results reported in Column 3, domestic firms' female labor share is positively correlated with FIEs' output share across industries, even after controlling for firm and year fixed effects. The correlation is

[38] As the managers (legal representative) of firms did not change 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 a firm's having a female manager is the dependent variable, we use the 2004 cross-sectional sample for the analysis.

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

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.

economically significant – a one standard deviation increase in FIEs' share in an industry's output is associated with an average increase of 0.7 percentage points in 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 summary, the cultural spillovers from FIEs documented so far seem to come mainly from the multinationals whose home culture is more favorable for women, supporting Proposition 4.

To investigate if geographic proximity matters in cultural spillovers, 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 in other provinces. Column 5 clearly shows that the spillover effect is stronger when FIEs are located in the same region. An F-test indicates that the difference in the corresponding coefficients is statistically significant. These results support our theoretical hypothesis that demonstration is an important mechanism through which the original culture is disseminated to local firms.

In Column 6, we include an interaction term between 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 successful FIEs. This finding is consistent with the learning part of our theoretical model, which emphasizes that profit maximization is a key motivation for learning among Chinese domestic firms.

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

In Table 5, we measure the prevalence of FDI using FIEs' output share in a city instead of an industry. Similar to our results at the industry level reported in Table 4, we find that both domestic firms' female labor share and probability 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 ratio and Herfindahl index. Specifically, the coefficient of 0.092 in Column 3 implies that a one standard deviation increase in FIEs' output share in the same city (0.182; see Table 1) is associated with an average increase of 1.7 percentage points 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 in 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 output. 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 has an effect, 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. In addition, firms in the same city but in different industries are unlikely to be competitors in the same final goods market. Many FIEs in China are also export-oriented and do not compete directly with local firms in domestic market. Thus, the spillover effect from FIEs to domestic firms in the same city is unlikely to be only due to increased competition from FIEs.[39]

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) for examining resource misallocation, the first-order conditions of firm i's profit maximization imply that the various firm-specific unobservable distortions can be measured with data as[40]:

$$1+\tau_{Kij} = \frac{1-\alpha_j}{\alpha_j\left(1-\beta_j\right)} \frac{w_m m_{ij}}{r k_{ij}}; \tag{17}$$

$$1-\tau_{Yij} = \frac{1}{\eta\alpha_j\left(1-\beta_j\right)} \frac{w_m m_{ij}}{R_i}; \tag{18}$$

$$1+\gamma_{ij} = \frac{\beta_j}{1-\beta_j} \frac{w_m m_{ij}}{w_f f_{ij}}. \tag{19}$$

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

[39] 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 share are less likely to exit in response to an increase in FDI in the same market, which supports Becker's (1957) seminal hypothesis. Such adjustments raise firms' profits but more importantly, reduce the misallocation of resources at the industry and national levels, thus raising aggregate efficiency.

[40] 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% of the tails of the distributions of $\log(1+\tau_{Ki})$, $\log(1-\tau_{Yi})$, and $\log(1+\gamma_i)$.

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_{ij} 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 three-digit (CIC) industries based on the female labor share of 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 more details).

2. We obtain the capital cost shares, $1-\alpha_j$, at the NAICS six-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 three-digit CIC industries. As our industry classification is broader than that of Hsieh and Klenow (2009) (who consider over 400 four-digit industries), we impose $\sigma = 2$, instead of 3 as they did.[41] 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.
3. We 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, using 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 of 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 $\overline{\varphi}_j = \left[\sum_{i=1}^{N_j}\varphi_i^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$.[42] In the second exercise, we assess 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 investigate 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. We

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

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

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

All numbers are 100×((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.

compute the ratio of TFP in the presence of both output and gender distortions (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 gain $\left(100 \times \left(\frac{TFP^e}{TFP} - 1\right)\right)$ 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% of aggregate TFP gain 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 (while keeping gender discrimination), the estimated TFP gain for the two years fall to about 95% and 91%, respectively. In other words, as reported in Column 4, gender discrimination accounted for about 5% of China's aggregate TFP loss during the sample period.

For comparison, we report the associated TFP gain when output distortions and gender discrimination are removed, while keeping the 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.[43]

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 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 have an effect. Fig. 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 three-digit industries.

Through the lens of our model, we can ask: what would happen to gender inequality and the associated TFP loss 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 is 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.[44] 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 the dispersion of $\log(1+\gamma)$ are about 9.6% and 19.2% of the observed

[43] With firms' endogenous entry and exit, the conditional mean of $\ln(1+\gamma)$ will be different between efficient and distorted TFP. Thus, the change in the mean of $\ln(1+\gamma)$ due to cultural spillovers will also matter.
[44] These numbers are obtained by computing $(-0.929)\times(-0.34)\approx 0.32$ and $(-0.929)\times(-0.17)\approx 0.16$, respectively.

Table 7
Correlation between FIEs' output share and the dispersion of Firms' gender discrimination.

Sample:	(1) 2005–2007	(2) 2006–2007	(3) 2007
Dependent Variable:	$\Delta_{t,t\text{-}1}SD(\log(1+\gamma))$	$\Delta_{t,t\text{-}2}SD(\log(1+\gamma))$	$\Delta_{t,t\text{-}3}SD(\log(1+\gamma))$
$\Delta_{t,t\text{-}k}$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

Observations are at the sector-year level. $\Delta_{t,t\text{-}k}$ 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.

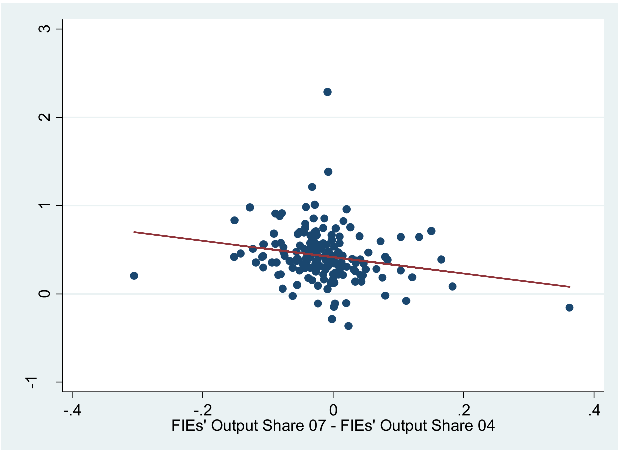

Fig. 3. Long diff in standard deviation of $\log(1+\gamma)$ and multinationals' output share by sector (2004–2007). (Source: NBS annual survey of industrial firms (2004) and authors' calculation.)

dispersions during the sample period, which will also be their respective contributions to the potential TFP loss due to gender discrimination.[45] Thus, the cultural spillover effect contributes about 1% (i.e., 19% of 5%) of the aggregate TFP gain during the sample period.

6. Concluding remarks

We demonstrate how economic globalization can change country-specific long-standing prejudices against women. We empirically examine whether and how multinational firms transmit gender norms across countries. Using Chinese manufacturing firm data from the 2004–2007 period, we find that foreign affiliates with a more gender-equal culture in their home countries tend to hire relatively more women and at the same time are more likely to hire women as their managers. Foreign firms, especially those from countries with a more gender-equal culture, also have a cultural spillover effect on domestic firms, as revealed by a positive correlation between domestic firms' female labor share and the prevalence of FDI across industries or cities. Our empirical results remain robust after controlling for firm fixed effects and a wide range of time-varying firm characteristics.

We create a model that considers firm heterogeneity in productivity and bias toward female workers, in addition to their comparative advantage in skill-based rather than physically intensive tasks. Consistent with the model's predictions, we find evidence that domestic firms respond to increased FDI by employing more women, probably due to imitation. Such cultural spillovers are stronger in the more female labor-intensive industries. We also find that the profits of discriminating firms suffer.

Using our model, we quantify the aggregate TFP loss due to discrimination against women, and the extent to which FDI alleviates this loss 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 contribute a 1% increase in aggregate manufacturing TFP. Our results reveal an under-explored cultural externality of FDI, in addition to the technology spillovers that have been the focus of the literature.

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

Many developing countries have recently made important progress toward gender equality and women's empowerment. Has the gender cultural spillover effect of FDI significantly contributed to this success? Should we expect similar FDI cultural spillover effects in other developing countries with different historical, cultural, and institutional backgrounds?[46] A deeper understanding of the mechanisms and pre-conditions of cultural spillovers is needed, and thus we leave these important questions for future research.[47]

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2021.103518.

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[46] For example, Ross (2008) shows that oil-rich countries in the Middle East have lower female labor participation than their oil-poor counterparts, which contributes to patriarchal norms and political institutions that slow down progress toward gender equality.

[47] For example, if the spillover mechanism is through labor turnover, then having a female labor force with sufficient human capital could be a pre-condition for this mechanism to occur.

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