Learning from International Trade: Asymmetric Cultural Transmission and Gender Discrimination

Danyang Zhang

Purdue University

Abstract

In this paper, I propose that international trade helps alleviate gender discrimination. With imperfect information on workers' ability, there is statistical discrimination towards female workers. Through international trade, culture transmits asymmetrically between firms located in countries with different gender cultures. This cultural transmission benefits women because it transmits only in one direction from more gender-equal cultures to less gender-equal cultures. I prove this by linking the Customs data to the Industrial Firms data of China in 2004, and find that Chinese firms trading with more gender-equal cultures hire a higher fraction of female workers and enjoy higher profits. Similar patterns are not found in Chinese firms trading with less gender-equal cultures. The impact of cultural transmission goes beyond the firms engaged in international trade to have spillover effects onto purely domestic firms. Comparing across skill groups, cultural transmission benefits high-skill female workers most.

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I. Literature Review

To the best of my knowledge, the closely related papers are Tang and Zhang (2017), Bøler et al. (2018), Zhang and Dong (2008), Dong and Zhang (2009), Black and Brainerd (2004), and Maystre et al. (2014).

Tang and Zhang (2017) is the closest paper to mine, studying how FDI affects the employment of female workers through cultural transmission based on Chinese experience. One important difference is that here I propose and prove the asymmetric transmission of culture, which is the key of why trade can alleviate discrimination. In their paper, however, this asymmetry is not discussed. Comparably speaking, the countries having FDI in China tend to be concentrated in countries with better gender-equal culture than China while for export and import, the destination and origin countries are more dispersed in their gender-equal culture[1]. Another difference is that I model cultural transmission as update of information compared to spread of taste in their paper[2].

Bøler et al. (2018) studies how flexibility of working hours affects the relative wage for the exporters in Norway, but in many of the specifications, they control for the Gender Gap Index, which is also used in my paper. In their paper, they control GGI to consider the difference in in women's social status between Norway and the destination country in case this makes female employees in Norway harder to do business with customers in those destination countries. Our papers are different in the following aspects. Firstly, their paper stresses the flexibility of working hours as the reason for wage difference while mine stresses the gender discrimination as the underlying reason. Secondly, their paper only studies relative wage while mine studies both relative wage and employment, thus having a more complete picture of female workers' labor market outcomes. Thirdly, I propose and proves the asymmetric transmission of culture. In their paper, GGI is never significant while in my paper I find strong evidence that culture transmission matters. The insignificance of cultural transmission in their results is exactly explained by the asymmetry of cultural transmission, which is established in my paper[3]. Lastly, their study is restricted within exporters but my paper also studies the spillover effects to the non-exporters, and I further distinguish the impacts on the direct exporters from the non-direct exporters.

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[1] For comparison of the FDI source country and trade partner countries, see Table A1 in the appendix.

[2] Though they mentioned that they also build a statistical discrimination model that has the same implications as the taste-based one, which would be available upon request.

[3] This is because Norway is one of the best countries in respecting women, ranking 2nd among the 115 countries in GGI in 2006. As a result, most countries have a worse gender-equal culture than Norway and thus cultural transmission does not take place. Comparably speaking, China is a better country to study asymmetric of cultural transmission since it ranks 63 among the 115 countries surveyed, having many countries on both sides.

Zhang and Dong (2008) and Dong and Zhang (2009), they compared female workers' productivity-adjusted relative wage across different firm types in China. Compared to my paper, they only find that exporters pay female workers higher relative wage without explaining why this is the result. They do not specify cultural transmission as the potential mechanism as in my paper, and they simply compared exporters to other type of firms without further disguising the destination countries, which is done in my paper. Another drawback of their paper is that the sample size is too small so the result might suffer from limited representativeness and estimation power[4], while the sample used in my paper is much larger.

Black and Brainerd (2004) tests one of the Becker (1957) predictions. It shows that faced with trade shocks, the residual gender wage gap in concentrated industries decreases more than that in the competitive industries. The mechanism they test in their paper is that competition can limit employers' ability to discriminate female workers, while in my paper trade affects the labor market through transmission of culture. Both of our papers study how trade affects the labor market, but the underlying mechanisms in two papers are completely different[5]. Moreover, their study is on industry level, comparing concentrated industries with competitive industries, while my study is on firm level, making within-industry comparisons.

Maystre et al. (2014) studies trade's role in the transmission of culture. But compared to my paper, their paper focuses on how trade liberalization biases people's preference while mine stresses trade's impact on the labor market. They study how culture changes and they stop there, but in my paper, change of culture is only the underlying mechanism, and I care more about how the change of culture further affects the labor market. The important result of their paper is that trade liberalization will shift local culture to global ones, thus leading to cultural convergence. My major conclusion is, however, that trade can improve female worker's labor market outcome through alleviation of discrimination. The underlying stories are also different: they assume that culture is attached to certain products so it is through consumption decision that people's cultural preference changes while in my paper cultural transmission happens through interaction of firms.

The contribution of this paper is that it finds another potential mechanism of how trade affects exporting country's labor market — through asymmetric cultural transmission. It proposes and proves, through both a simple model and empirical results, the fact that trade can alleviate the gender discrimination by improving women's employment and wage in the exporting country. It further stresses that the asymmetric transmission of cultural is the key to this result — by interacting with importers in countries with more gender-equal culture, the exporter would be less

[4] Their sample only includes about 2000 firms in total and located in only 5 cities in China.
[5] In my paper, I include industry HHI to control for competition.

discriminative towards female workers; however, interacting with importers from less gender-equal cultures will not make exporters more discriminative to female workers. In this paper, under a statistical discrimination set-up, this asymmetry is a natural result of the information updating for exporters.

II. Model

Phelps (1972) is the first paper which establishes a simple model about statistical discrimination. Overtime, this model has been developed, modified, and applied in many discrimination papers. The model I propose here in my paper is also based on statistical discrimination.

It is assumed that due to the existence of searching cost, each period one worker is only randomly matched to one firm[6] (Note that in this paper firms and not distinguished from employers, and they would be used interchangeably in the following discussion). All workers live for only one period.

Suppose all firms have the same task that a worker is either qualified or not qualified for, which is denoted by indicator variable I.

$$I_i = \begin{cases} 1 & \text{if worker i is qualifed for the task} \\ 0 & \text{if worker i is not qualifed for the task} \end{cases}$$

If worker is qualified, the a positive payoff μ_q is generated; otherwise, a negative payoff of μ_n is generated.

The proportion of workers who are qualified for the job is denoted by q, which falls between 0 and 1. For simplicity, male and female workers are assumed to have the same q such that they are equally productive in general. (However, this assumption can be easily relaxed without changing any predictions from the model.) Firms observe q but they do not observe each worker's qualification. Instead, they receive a signal S_i revealing worker i's type, and then make hiring decision solely based on the value of signal. The signal is either good or bad, and firms only hire workers with a good signal.

The quality of the signal is denoted as P, which equals the probability that the signal is correct. A higher P then means the signal is of better quality.

$$P = prob(S_i = good \mid I_i = 1) = prob(S_i = bad \mid I_i = 0)$$

In Aigner and Cain (1977), Lundberg and Startz (1983), and Oettinger (1996), they all assume that the test score equals a worker's true ability plus an error term, and the variance of the error term is larger for the black workers. As a result, the test score is less reliable for the black workers compared to their white counterparts. Following their idea about the difference in the reliability of signal across races, in my paper I apply this assumption on genders such that men have better information quality. In my model, instead of a test score, I simplify the information

[6] Specifically, each period one worker can only be matched to one firm, but one firm can be matched with multiple workers. The number of workers matched to a firm, however, is exogenously given and out of firms' control.

into a signal taking on only two values, and P is the only variable that controls the reliability of the signal. Therefore, I assume that the quality of signal is better for men than for women such that men have a higher P. For standardization, I assume P=1 for men, hinting that a firm can perfectly observe whether a man is qualified or not[7]. For women, however, I assume 0<P<1 to reflect the lack of experience in assessing women's capability (compared to men). As a result, all the male workers hired are actually qualified, while there are some hired female workers who are not qualified. For notation simplicity in the following analysis, the proportion of hired female workers who are actually qualified is denoted as T.

$$T = prob(I_i = 1 \mid S_i = good) = \frac{Pq}{Pq + (1-P)(1-q)}$$

Note that T is increasing in P, so that firms with better signal end up having higher proportion of qualified female workers among the hired ones.

$$\frac{\partial T}{\partial P} = \frac{q(1-q)}{\left[Pq + (1-P)(1-q)\right]^2} > 0$$

To insure that the signal is actually informative, P needs to be large than a half. This is because firms always have the outside option of not using the signal at all and randomizing the hiring decision for women. Therefore, to make the signal useful, we need T to be larger than the randomized outcome. Note that in the randomized case, the proportion of actually qualified women among the hired ones simply equals the true proportion of qualified women, which is q.

$$T = \frac{Pq}{Pq + (1-P)(1-q)} > q \Rightarrow P > \frac{1}{2}$$

With the basic set-up of the model above, now I turn to the analysis of the implications from this model.

i. Employment fraction

We first study the employment fraction of women within a firm. Here I use L_m and L_f to denote the number of male and female workers hired by firms, and M and F to denote the number of male and female initially matched to firms, respectively. Note again that for men, due to the existence of perfect signal, all qualified male workers would be hired; for women, however, only those who send the good signal are hired despite of their true qualification.

$$L_m = M * prob(S_i = good) = Mq$$
$$L_f = F * prob(S_i = good) = FPq + F(1-P)(1-q)$$

[7] A more natural and less restrictive assumption could be that P for men also lies between 0 and 1, but is larger than P for women. However, this will not change the nature of our analysis or predictions of this model but only adds in extra coefficients here and there. Therefore, to keep the model in a simpler form, P=1 is assumed for men.

Within a firm, the female employment fraction S would then be:

$$S = \frac{L_f}{L_f + L_m} = \frac{Pq + (1-P)(1-q)}{Pq + (1-P)(1-q) + \frac{M}{F}q}$$

Here note that M/F is exogenous to firms and varies between industries and regions[8]. Within an industry and region, M/F is fixed. It is then obvious from the above equation that the female employment fraction is decreasing in the male-female ratio in an industry. Moreover, female employment fraction is an increasing function of information quality P as long as over half of the female applicants are qualified, which I would assume to be true.

$$\frac{\partial S}{\partial P} = \frac{(2q-1)q}{\left(Pq + (1-P)(1-q) + \frac{M}{F}q\right)^2}\frac{M}{F} > 0 \text{ as long as } q > \frac{1}{2}$$

ii. Relative Wage

Now we analyze the implication for relative wage of female over male workers derived from this model. The payment schedule is designed as follows: employers and workers bargain over the wage, and any payoff of firms are shared between workers and employers. Therefore, employer would hire a worker as long as he/she generates a positive expected payoff (in our model, the hiring decision is made solely based on the signal, so whoever gives a good signal generates positive expected payoff, while those who give a bad signal generate negative expected payoff. Conditions are discussed in appendix A. 1. which guarantees the validity of this statement). In this payment schedule, neither workers nor employers have the incentive to deviate[9]. Sigma is defined as the share of payoff, which falls between 0 and 1, that is enjoyed by the worker. The wage of a worker is simply the product of δ and his/her expected payoff, as is defined below. (Note that since the employers know q, it can also derive the true T, which is the probability that a hired female worker is actually qualified).

$$w_m = \delta\mu_q$$
$$w_f = \delta\left(T\mu_q + (1-T)\mu_n\right)$$

It is obvious that

$$w_m = \delta\mu_q > \delta\left(T\mu_q + (1-T)\mu_n\right) = w_f \text{ since } \mu_q > \mu_n$$

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[8] The matched male-female worker ratio varies across industries to reflect the fact that some industries might more intensively use female labor than other industries. It also varies across regions to reflect the variation of gender composition in local labor supply.

[9] For an employer, the only decision he can make is whether to offer a worker the job. If he refuses to offer the job to a worker with good signal, then he gets 0 payoff while he could have got a positive expected payoff. If he offers the job to a worker with bad signal, then he gets negative expected payoff instead of a 0 payoff. For a worker, the only decision he can make is whether to accept the job offer. If he declines the offer, he then gets a 0 payoff while he could have got a positive payoff, which is his wage. Therefore, neither the employer nor the worker has the incentive to deviate.

Therefore, female workers receive lower wages than male workers with imperfect information, and relative wage of female workers over male workers, R, can be derived.

$$R = \frac{w_f}{w_m} = \frac{\delta\left(T\mu_q + (1-T)\mu_n\right)}{\delta\mu_q} = T + (1-T)\frac{\mu_n}{\mu_q}$$

This relative wage is then increasing in P.

$$\frac{\partial R}{\partial P} = \frac{\partial R}{\partial T}\frac{\partial T}{\partial P} = \left(1 - \frac{\mu_n}{\mu_q}\right)\frac{\partial T}{\partial P} > 0$$

Therefore, firms with higher P give women higher wages relative to men.

Note that since workers only live for one period, after one period all current workers exit the model and firm rehire new workers. Therefore, there would be no information updating across periods in this model.

iii. Profit

For an employer, its profit is the sum of shared payoffs from all workers:

$$\pi = Mq(1-\delta)\mu_q + F(1-\delta)\left(Pq\mu_q + (1-P)(1-q)\mu_n\right)$$

Profit per worker, U, is then written out as:

$$U = \frac{\pi}{L_m + L_f} = (1-\delta)\mu_q + (1-\delta)(\mu_n - \mu_q)\frac{(1-P)(1-q)}{Pq + (1-P)(1-q) + \frac{M}{F}q}$$

Given M and F, a firm's profit per worker is increasing in P:

$$\frac{\partial U}{\partial P} = \frac{(1-\delta)(\mu_q - \mu_n)(1-q)q(1+\frac{M}{F})}{\left(Pq + (1-P)(1-q) + \frac{M}{F}q\right)^2} > 0$$

Therefore, firms with better information quality would be more profitable.

As comparison, a taste-based discrimination model is briefly described in the appendix A.2, which would generate different predictions compared to the statistical discrimination model I use in my paper.

iv. Trade and Learning

As is mentioned above, P reflects the ability of the firm to correctly estimate a female worker's capability, specifically, whether the female worker is qualified for the task or not. A higher P means a firm makes better estimate of a female worker's ability. I therefore assume that in countries with more gender-equal culture, firms have better information about a female worker's true ability since the gender gap is smaller and thus firm are more experienced in dealing with female workers.

By exporting to firms in other countries, the exporters are assumed to be able to observe and learn how the importing firms estimate their female workers, but with a discount factor F(.), which lies between 0 and 1. F(n) is an increasing function of interaction between exporters and importers, and n reflects the intensity of interaction, which could be number of interactions in reality. Since the profits of a firm is increasing in P, an exporter then has the incentive to update its own information after it observes how an importer gets its workers' signals. Exporters will compare its own signal and the importer's signal according to the information quality, and choose the signal with higher P.

$$P_{\text{exporter}}' = \max\left\{P_{\text{exporter}}, F(n) * P_{\text{importer}}\right\}$$

Therefore, by exporting to firms in destination countries with more gender-equal culture, exporters might be able to update its signal quality to have a better estimate of a female worker's true capability. However, firms which export to countries with worse gender-equal culture would have no updates in P since their own signal has better quality than the importer's, so they would continue adopting their original signal.

Moreover, since the cultural transmission takes place through firms' interactions, this cultural transmission process could also happen between exporters and non-exporters with interactions. There would then be spillover effects on the non-exporters which are in the same industries or regions with the exporters.

$$P_{\text{non-exporter}}' = \max\left\{P_{\text{non-exporter}}, P_{\text{exporter}}'\right\}$$

v. Comparison between Different Skill Groups

I then compare different skill groups. Suppose that both men and women are divided into two subgroups based on some characteristics (e.g. education), with one group having higher proportion of qualified workers. Note that the assumption that men and women are equally productive is kept so that the true proportions of qualified workers of each subgroup are still identical across genders. Here we use H to denote the group with higher fraction of qualified workers q_H (the high-skill group), and L to denote the subgroup with lower fraction of qualified workers q_L (the low-skill group).

For the female employment fraction in a firm, it can be derived that:

$$\frac{\partial S}{\partial q}=\frac{-\frac{M}{F}(1-P)}{\left(Pq+(1-P)(1-q)+\frac{M}{F}q\right)^2}<0$$

Since $q_H > q_L$, it is then predicted that the female employment fraction within the high-skill groups should be lower than that of the low-skill group.

I then study how female employment fraction react to the change in P differently across skill groups. Taking the cross derivative with respect to P and q:

$$\frac{\partial^2 S}{\partial P\partial q}=\frac{(4q-1)(1-P)+q(2P-1)+\frac{M}{F}q}{\left(Pq+(1-P)(1-q)+\frac{M}{F}q\right)^3}>0 \text{ when } q>\frac{1}{2} \text{ and } P>\frac{1}{2}$$

Note that we have already derived above that the female employment fraction is increasing in P. Combining these two results, the female employment fraction increase more when q is higher. Therefore, with $q_H > q_L$, it is expected that when exporting to firms with better gender-equal culture, the female employment fraction among the high skill group would have larger increase than the low skill group.

Similar analysis is carried out for the relative wage:

$$\frac{\partial R}{\partial q}=\frac{\partial R}{\partial T}\frac{\partial T}{\partial q}=(1-\frac{\mu_n}{\mu_q})\frac{P(1-P)}{\left(Pq+(1-P)(1-q)\right)^2}>0$$

$$\frac{\partial^2 R}{\partial P\partial q}=\frac{(1-2q)\left(Pq+(1-P)(1-q)\right)-2q(1-q)(2P-1)}{\left(Pq+(1-P)(1-q)\right)^3}<0 \text{ when } \frac{1}{2}<q<1 \text{ and } P>\frac{1}{2}$$

Since $q_H > q_L$, based on the above results, comparing with the low-skill group, high-skill group have larger relative wage of female workers over male workers but smaller increase in relative wage when exporting to firms with better gender-equal culture.

vi. Implications from the Model

The testable implications from this model are summarized below:

Implication 1

Female employment fraction within a firm is higher for the low-skill workers compared to the high-skill group. The relative wage of female workers over male workers, however, would be larger for the high-skill group.

Implication 2

Trading with firms in countries with larger P (more gender-equal culture) would make the exporters/importers hire a higher fraction of female workers, pay female workers higher relative wage, and have higher profits. However, trading with firms located in countries with smaller P (less gender-equal culture) would have no impact. The impact of cultural transmission through trade on the labor market is thus asymmetric.

Implication 3

When trading with firms with larger P, the female employment fraction increases more in the high-skill group. Relative wage, on the other hand, increases more in the low-skill group.

Implication 4

Cultural transmission through trade would have spillover effects on the firms not engaged in international trade (purely domestic firms).

III. Data

i. Data Introduction

In this paper we use multiple databases, but the primary data comes from Chinese Customs Database, the Chinese Industrial Firm Database and the Global Gender Gap Report 2006

The Chinese Customs Database provides transaction-level data on imports and exports. It contains information including date of transaction, quantity, price, 8-digit HS code, destination country/region and name, ownership and ID of the firm.

The Chinese Industrial Firm Database is a firm-level database constructed by the National Bureau of Statistics in China[10]. It records firm's basic information (e.g. name, phone number, location, industry, etc.), financial status (capital, inventory, profit, total wage, etc.) and other information related to production and sales (output, sales, employee number, etc.). It surveys all industrial firms in the mainland of China with sales higher than 5 million RMB[11], covering firms in mining, manufacturing and production and supply of electricity, gas, and water industry.

Gender Gap Index (GGI) comes from the Global Gender Gap Report 2006 provided by World Economic Forum[12]. GGI covers 115 countries with over 90% of the world's population. It is composed based on 14 ratios on gender gap classified into four sub-indexes: economic participation and opportunity, education attainment, health and survival, and political empowerment (see Table A2 in appendix for detailed information on how GGI is constructed). GGI lies between 0 and 1, where a higher index means more gender-equal culture. The top and bottom 10 countries with respect to GGI value is listed in Table 1 (for the full rank, see Table A*3*). Among the 115 countries, China ranks 63 with GGI value of 0.656. The fact that China ranks almost in the middle of the GGI distribution gives me enough space to test the asymmetric transmission of culture. For distribution of all countries with GGI data, see Figure 1.

[10] Each record corresponds to a legal unit. For the detailed information on legal unit, see Brandt et al. (2012)

[11] About 604098 dollars using the 2004 exchange rate of 8.2768 between RMB and dollar. (Exchange rate data comes from World Bank at https://data.worldbank.org/indicator.) However, 5 million RMB is not a hard rule. See Brandt et al. (2012) for detailed information on this.

[12] See https://www.weforum.org/reports/the-global-gender-gap-report-2017. Boler et al. (2018) also use GGI to measure gender culture.

Table 1: Top and Bottom 10 Countries/Regions in GGI Value

Top 10 countries			Bottom 10 countries		
Rank	Country	GGI	Rank	Country	GGI
1	Sweden	0.8133	106	Mauritania	0.5833
2	Norway	0.7994	107	Morocco	0.5826
3	Finland	0.7958	108	Iran	0.5802
4	Iceland	0.7813	109	Egypt	0.5785
5	Germany	0.7524	110	Benin	0.5778
6	Philippines	0.7516	111	Nepal	0.5477
7	New Zealand	0.7509	112	Pakistan	0.5433
8	Denmark	0.7462	113	Chad	0.5246
9	United Kingdom	0.7365	114	Saudi Arabia	0.5241
10	Ireland	0.7335	115	Yemen	0.4594

Notes: Data from Global Gender Gap Report 2006

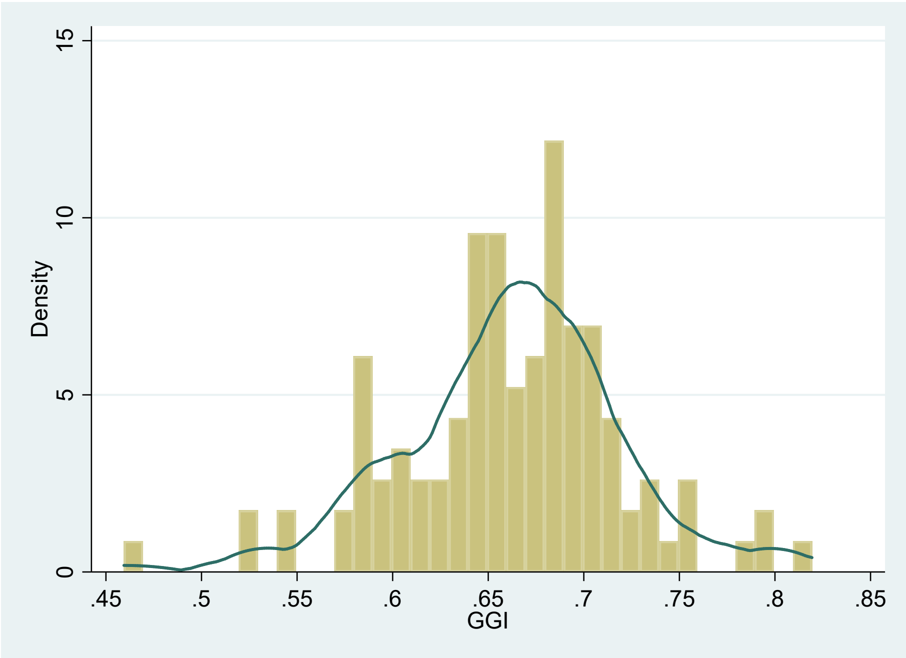

Figure 1: Distribution of GGI

ii. Treatment of Data

I first merge customs data with GGI data according to country name. Based on the records in the customs data, China exports to 229 destinations and imports from 210 origins in 2004, both covering all the 114 countries with GGI data[13]. Note that in Chinese customs data, Hong Kong, Macao and Taiwan (for simplicity, HMT), three regions in China, are listed as exporting destinations or importing origins. Since all three regions are part of China, they do not have their

[13] Since China is among the 115 countries and regions with GGI data, for Chinese firms, there are only 114 destination/origin countries with GGI data to trade with.

own GGI value, but 19.66% of the export value and 13.70% of the import value (measured in dollars) are between HMT and other regions in China. To keep those transactions in my dataset, I impute the GGI value of HMT[14]. In the baseline analysis, I assume that HMT has the same GGI value as China mainland[15]. For all other countries that China trade with but do not have GGI value, altogether they only account for 2.02% of the export value and 2.67% of the import value in 2004. Therefore, exclusion of those transactions will not be a big problem when using GGI data. Based on this merged customs-GGI database, I construct the firm-level information quality index (the P in my model) or discrimination index, which is the maximum GGI of the origin/destination with which a Chinese firm trades.

I then merge the customs-GGI database with the industrial firms' database. Unfortunately, the identification number of firms in Customs Database and Industrial Firm Database are constructed in different ways and cannot be matched. Following Yu and Tian (2012) I adopt the two-step matching. In the first step, I match the two databases based on firm name with 52,309 successful matches (46,243 for exporters and 37,299 for importers, separately[16]). In the second step, for all unmatched firms in the first step, I then match them based on the last seven-digit phone number and postcode[17], which successfully matches another 2,064 firms (1,919 for exporters and 1,456 for importers, separately). Applying this matching method, about 53.16% of the trade value in 2004 is successfully matched, with a higher matched fraction for export (56.65%) than import (49.88%). The reason for the low matching fraction is twofold: firstly, as I have mentioned above, Industrial Firm Database only covers firms with sale over 5 million RMB, so that the exporters/importers with less sales cannot be matched; secondly, there are purely trading firms in China that serve only as intermediaries without doing production, and thus are not included in the Industrial Firm Database either. The GGI-customs-industrial matched database is then my final sample to use. As is discussed in Brandt et al. (2012), I drop the firms with fewer than 8 workers since these firms are under a different legal regime. See Table 2 for the summary statistics of the final sample.

[14] In one of the robustness checks, however, I exclude HMT trade to show that my results are not driven by the inclusion of HMT trade.

[15] In one of the robustness checks, I impute the GGI value for HMT using their historical background. See the discussion in robustness check for how the imputation is done.

[16] Note that the sum of numbers of successful match using exporters only and importers only is larger than the successful match using both exporters and importers. This is because many firms are both exporters and importers.

[17] Based on the final sample in my paper, there are 21533 distinct postcodes.

Table 2: Summary Statistics

	Exporters and Importers						Local Firms		
	More			Less					
	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.
female fraction	45,988	0.497	0.239	8,035	0.479	0.259	215,197	0.377	0.237
female fraction (high)	44,065	0.382	0.236	7,468	0.376	0.268	175,676	0.285	0.260
female fraction (low)	45,787	0.505	0.260	8,004	0.484	0.280	214,504	0.383	0.251
skill ratio	45,988	0.151	0.183	8,035	0.142	0.174	215,197	0.116	0.161
firm age	45,988	8.864	8.481	8,035	7.816	8.132	215,197	9.765	10.925
firm size	45,988	462	1577	8,035	222	1103	215,197	199	976
output	45,988	171	1167	8,035	55	239	215,197	53	532
computer count	45,988	47	505	8,035	15	96	215,197	12	140
foreign capital	45,988	0.276	0.413	8,035	0.349	0.437	215,197	0.026	0.144
HMT capital	45,988	0.263	0.416	8,035	0.181	0.365	215,197	0.038	0.176
GGI	45,988	0.750	0.033	8,035	0.639	0.018			
processing trade	45,988	0.332	0.420	8,035	0.205	0.365			
destination number	45,988	9.941	9.535	8,035	1.594	0.953			

Notes: Skill ratio is the fraction of high-skill workers in all employee, where high-skill workers are defined as workers with a college degree, bachelor's degree, master's degree or above. The low/high skill female ratio is measured by the number of female low/high skill workers over the number of all low/high skill workers in a firm. Foreign fraction and HMT fraction are the fractions of capital that come from foreign countries and Hong Kong, Macao and Taiwan, separately. Firm age is the number of years a firm has operated. Firm size is the number of employees in a firm. Output and export are measured by monetary value in million RMB. GGI is the maximum of the destination GGI, as is used in the main regressions. Processing trade is the fraction of trade value that is processing trade.

According to Table 2, as is shown in previous literature about exporters' characteristics, the exporters in my sample are on average larger, produce higher output, hire more skilled workers, and depend on FDI more (both from foreign and from HMT) as their capital resources. One thing to note is that exporters also have a higher fraction of female workers, both for high and low skill. Comparing the second and third row, the statistics shows that the female employment fraction among the high skill group is lower than that of the low skill group for both exporters and all firms, which supports *Implication 1* from my model.

IV. Empirical Approach and Results

i. Empirical Approach

Due to the limitation of data, I cannot directly observe the wage bill and other personal characteristics of each individual worker, so I cannot decompose the wage into the explained and unexplained part as some of the typical discrimination paper do in their empirical analysis section. In my paper, instead, female employment fraction and relative wage are used as a reflection of the level of statistical discrimination.

To see how discrimination affects the female employment ratio in a firm, we run the following regression:

$$female\_fraction_i = \alpha + \rho GGI_i + V\lambda + \beta_{industry} + \delta_{region} + \varepsilon \qquad (1)$$

Here the dependent variable is the female employment fraction in each firm i. GGI is the destination information quality faced by each exporter, and thus regression (1) uses sample covering only the exporters. Industry and province fixed effects are included to take into consideration the selection across industries and regions. V is firm-level control variables including skill ratio, output, firm age, firm size, output, processing trade, ownership. See appendix A. for how these control variables are constructed.

ii. Empirical Results

(i) Basic Results

The basic regression results are listed in Table 3[18]. The industry fixed effects are included at 2-digit level (39 industries) and regional fixed effects are at province level (31 provinces in the mainland of China). Note that it is of great importance to control for industry and province fixed effects, since there would be selection across industries and provinces. For calculation of GGI, I take into consideration of HMT's historical background. Historically, all these three regions have been seized and colonized by other countries: Taiwan is colonized by Japan (with GGI 0.645, ranks 79) during 1895-1945, Hong Kong is colonized by United Kingdom (with GGI 0.737, ranks 9) during 1842-1997, and Macao is colonized by Portugal (with GGI 0.692, ranks 33) during 1553-1999. I therefore impute these countries GGI value for HMT. In robustness checks, I also

[18] Note that firms with all workers of the same gender are always excluded. For one thing, the matched male-female worker ratio cannot be 0 or infinity. For another, these firms are not responsive to the change in information quality at all.

impute China's GGI value for HMT or simply drop all transactions with HMT. The results don't change much.

The fixed effects are not included in column (1) but included in column (2), but the coefficient doesn't change much with inclusion of the fixed effects. Based on the results, trading with more gender-equal cultures would increase the female fraction within a firm overall, as is predicted by the model. However, when I further distinguish trade to countries with more gender-equal cultures from the less gender-equal cultures compared to China, it shows that the positive effects trade has on female fraction is driven merely by trading with more gender-equal cultures. Trading with less gender-equal culture, however, would have no impact. This supports our main prediction from the model that the transmission of culture is asymmetric since update of information only happens when the new information is better than the existing one. To save space, in other regression I would only report the variables of interest.

Table 3: Trade and Female Fraction

	Female Fraction			
	All	All	More	Less
GGI	0.147***	0.146***	0.162***	-0.0225
	(0.0292)	(0.0217)	(0.0328)	(0.129)
GGI*Firm age	-0.00345***	-0.00207***	-0.00209***	-0.00205***
	(0.000266)	(0.000206)	(0.000211)	(0.000642)
ln(Output)	-0.0568***	-0.0438***	-0.0440***	-0.0396***
	(0.00204)	(0.00146)	(0.00156)	(0.00288)
ln(Firm Size)	0.0878***	0.0633***	0.0635***	0.0607***
	(0.00250)	(0.00188)	(0.00192)	(0.00409)
ln(Firm Age)	0.00460*	0.00959***	0.0107***	0.00316
	(0.00272)	(0.00241)	(0.00254)	(0.00538)
Skill Ratio	-0.185***	-0.134***	-0.132***	-0.148***
	(0.0122)	(0.00783)	(0.00845)	(0.0173)
Processing Trade	0.0647***	0.0477***	0.0439***	0.0678***
	(0.0139)	(0.00571)	(0.00605)	(0.00823)
FDI (Foreign)	0.0373***	0.0347***	0.0359***	0.0307***
	(0.00541)	(0.00392)	(0.00408)	(0.00732)
FDI (HMT)	-0.0149***	-4.31e-05	0.00378	-0.0160**
	(0.00570)	(0.00341)	(0.00357)	(0.00800)
ln(computer)	-0.0199***	-0.0114***	-0.0118***	-0.00732***
	(0.00231)	(0.00121)	(0.00125)	(0.00276)
Constant	0.198***	-0.00103	-0.0172	0.0885
	(0.0194)	(0.0717)	(0.0848)	(0.108)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes
Province Fixed	No	Yes	Yes	Yes
Observations	53,671	53,671	45,701	7,970
R-squared	0.213	0.448	0.438	0.514

Notes: Standard errors in the parenthesis, clustered at county level.

Since for the gender gap index, the most relevant sub-index is the "Economic Participation and Opportunity", I also run the basic regression using only this sub-index. See appendix for the results. Another potential problem is that people worry that the female employment fraction of the product might be correlated with the product quality, I hence further control for the product price. See appendix for results.

Another prediction the model makes is that firms with better information quality would enjoy higher profits. Here the dependent variable is basically the log of profits for a firm. Since there are some firms with zero or negative profits. To deal with this problem, the dependent variable is calculated as below[19]:

$$\text{outcome variable} = \begin{cases} \ln(\mathit{profit}) & \text{if profit} > 1 \\ 0 & \text{if } -1 \le \text{profit} \le 1 \\ -\ln(-\mathit{profit}) & \text{if profit} < -1 \end{cases}$$

Similar to Table 3, here all columns apart from column (1) have controlled for fixed effects. Based on the results, overall firms trading with more gender-equal culture enjoy higher profits. When we split the sample into trading with more and less gender-equal cultures, only firms trading with more gender-equal cultures enjoy higher profits.

For comparison, here I also use other two ways dealing the outcome variable. One is that for all firms with zero or negative profits, I impute 0.001 for their profits, and then take log based on the treated profits. The other way is that I add a constant to profits of all firms so that all firms now have positive profits, and then I take log of the treated profits[20]. The results are similar using the other two methods. For results of other two ways of dealing with log of profits, see Appendix.

Table 4: Profit

	ln(Profit)			
	All	All	Only Better	Only Worse
GGI	4.372***	3.475***	6.678***	2.393
	(0.660)	(0.614)	(1.030)	(4.036)
GGI*Firm age	-0.199***	-0.193***	-0.198***	-0.232***
	(0.0124)	(0.0123)	(0.0133)	(0.0294)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes
Province Fixed	No	Yes	Yes	Yes
Observations	52,951	52,951	45,063	7,888
R-squared	0.076	0.095	0.104	0.067

Notes: Standard errors in the parenthesis, clustered at county level.

[19] Note that in the final sample, there are not many firms lies within the profit range of (-1,1), so it is not a big problem treating all these firms having a 0 profit.
[20] In my paper, here I looked at the smallest profit a firm has, which is negative, and I add the absolute value of this number to profits of all firms.

(ii) Subgroups

As is shown in the model, groups with higher proportion of qualified workers should experience larger change in female fraction faced with change in information quality, which is Implication *3*. I then test this implication by dividing workers into high-skill and low-skill groups based on their education level. Those with a college degree, bachelor's degree, master's degree and above are classified as high-skill workers while other workers are classified as low-skill workers. Within each firm, I then calculate the female fraction for high-skill and low-skill workers and run regressions separately for each skill group.

Table 5: Trade and Female Fraction (by Skill Group)

	Female Fraction (High Skill)		Female Fraction (Low Skill)	
	Only Better	Only Worse	More	Less
GGI	0.226***	0.165	0.106***	-0.237
	(0.0307)	(0.132)	(0.0377)	(0.166)
GGI*Firm age	-3.26e-05	0.000466	-0.00247***	-0.00210***
	(0.000199)	(0.000680)	(0.000236)	(0.000736)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes	Yes
Observations	37,266	5,687	37,266	5,687
R-squared	0.136	0.156	0.415	0.482

Notes: Standard errors in the parenthesis, clustered at county level.

Based on the results in Table 5, trading with more gender-equal culture has significant effects on the employment fraction of female workers only for the high-skill group (for low skill group, the result is marginally insignificant with P value of 0.115), while trading with less gender-equal culture have on impact in both skill groups.

Comparing the coefficients in column (1) and column (3), it is obvious that trading with more gender-equal culture has larger impact on the female fraction for the high-skill workers, which supports *Implication 3* from the model.

(iii) Spillover Effects

Although the non-exporters and non-importers do not directly interact with firms in other countries, they do interact with the local exporters and importers in the same region or same industry, and thus there would be spillover effects for the firms not engaged in international trade. Similar with the case of exporters/importers, here the regional/industry GGI for the domestic firms is the maximum of exporter/importer GGI within a region/industry. The 6-digit area code is used as region identifier and there are 2846 distinct regions in the final sample, with only 68 regions (2101 firms) having regional GGI that is lower than China's GGI. As for industry, the 4-digit industry code is used, which contains 524 unique values, with only 3 industries (74 firms) having industry GGI lower than China's GGI. Since the numbers of regions and industries with less gender-equal culture than China are too small, here I do not split sample into "only more gender-equal culture" and "only less gender-equal culture" again. Instead, according to the model, for those regions and industries with GGI lower than China, I use China's GGI for these regions and industries since these firms will continue use their original information quality, which equals to the GGI of China in empirical analysis. The results of regional and industrial spillover effects are listed in Table *6*.

Table 6: Spillover Effects

	Female Fraction					
	Region			Industry		
	max	average		max	average	
		Better	Worse		Better	Worse
GGI	0.128***	0.143***	0.0409	0.505***	0.389	1.135
	(0.0314)	(0.0552)	(0.136)	(0.154)	(0.284)	(0.805)
GGI*Firm age	-0.00129***	-0.00142***	-0.000542*	-0.00123***	-0.00135***	0.000992
	(0.000115)	(0.000131)	(0.000300)	(0.000217)	(0.000238)	(0.00119)
Ownership	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211,038	193,513	17,525	211,038	210,395	643
R-squared	0.443	0.436	0.468	0.443	0.443	0.324

Notes: Standard errors in the parenthesis. Column (1) and (2) are clustered at county level, and column (3) and (4) and clustered at 4-digit industrial code level.

The basic pattern still holds for the spillover effects. That is, increase of female fraction occurs only in regions with regional GGI higher than China. One thing to note is that the industrial spillover effect is not significant for trading with more gender-equal cultures while regional spillover effect is. This might be that firms located in distant regions within the same industry do not really interact with each other, and thus there is not spillover effects within industry. Another problem of the industrial spillover effect is there are only 524 different industries at 4-digit level, with only 3 industries having average GGI lower than China, which makes the sample greatly unbalanced. The insignificant result might be driven by this mis-aggregation so results in the last two columns might be reliable to study for industrial spillover effects.

Based on the results, it is obvious that the cultural transmission does have spillover effects to firms in the same region.

iii. Robustness Check

In the robustness check, I use five other methods to calculate the GGI faced by each firm. The summary statistics of the main regression GGI and three robustness GGIs are listed in Table *7*.

Table 7: Summary Statistics for Different Calculation of GGIs

	Obs	Obs (better)	Obs (worse)	Mean	S.D.	Min	Max
GGI	54,023	45,988	8,035	0.73309	0.05053	0.5241	0.8133
GGI (China)	54,023	42,181	5,794	0.72521	0.05403	0.5241	0.8133
GGI (frequency)	54,023	42,181	5,794	0.72160	0.05167	0.5241	0.8133
GGI (no HMT)	51,783	42,181	8,787	0.72737	0.05457	0.4594	0.8133
GGI (no worse)	54,023	42,181	0	0.72736	0.05030	0.656	0.8133
GGI (dummy)	54,023	45,988	8,035	0.85126	0.35582	0	1

Notes: In the first row, GGI is used in the main regressions. It is the maximum of all origin/destination GGIs considering the historical background and impute the value of the countries that seized Hong Kong, Macao, and Taiwan before China formally took them back. The five other GGIs are alternative methods used in the robustness checks. GGI (China) imputes China's GGI for Hong Kong, Macao, and Taiwan. GGI (frequency) further uses the transaction frequency Chinese firms have with the origin/destination countries. GGI (no HMT) drop the transaction to Hong Kong, Macao and Taiwan. GGI (no worse) imputes the GGI value of China to all the firms trading with GGI index lower than China. GGI (dummy) is a dummy that takes 1 if the destination GGI is larger than China and 0 otherwise

Results are listed in Table *8*. In the first two columns, GGI (China) imputes China's GGI for Hong Kong, Macao, and Taiwan. For column (3) and (4), GGI (frequency) is calculated taking into consideration the transaction frequency. It is nature to think that Chinese firms cannot learn all their customers'/suppliers' information through one single transaction. Therefore, here I calculate the frequency of Chinese firms interact with some origin/destination country, and how much a Chinese firm can learn is an increasing function of the transaction frequency. The GGI is then calculated as the maximum of the origin/destination information that is successfully learned by the Chinese firms (see appendix for the detail calculation). For column (5) and (6), trade with Hong Kong, Macao and Taiwan are dropped compared to imputing other countries' GGI value as in the main regressions. For column (7), I impute China's GGI for all firms that end up trading with only less gender-equal cultures. In last column, instead of using the GGI value, I simply make trading with more or less gender-equal cultures a dummy variable, where trading with more gender-equal culture is 1.

From the comparison, we can see that the alternative GGIs resemble the GGI that is used in the main regressions. Once taking the transaction frequency into consideration, the GGI (frequency) is a bit lower than GGI, since now firms cannot learn all of trade partners' information through one single transaction.

Based on the results, the asymmetric cultural transmission pattern is quite robust to alternative calculations of GGI. Therefore, when Chinese firms trade with countries of more gender-equal culture, they would hire a higher fraction of female workers due to the update of information about individual female workers' ability. Trading with countries of less gender-equal culture, however, would have no impact.

Table 8: Trade and Female Fraction (Alternative GGI Calculations)

	Female Fraction							
	China for HMT		Frequency		Drop HMT		No Less	Dummy
	More	Less	More	Less	More	Less		
GGI	0.119***	0.0700	0.136***	0.0536	0.119***	0.131	0.108***	0.0221***
	(0.0306)	(0.115)	(0.0322)	(0.120)	(0.0306)	(0.112)	(0.0216)	(0.00298)
GGI*Firm age	-0.00207***	-0.00264***	-0.00209***	-0.00264***	-0.00207***	-0.00250***	-0.00207***	-0.00115***
	(0.000213)	(0.000545)	(0.000214)	(0.000544)	(0.000213)	(0.000592)	(0.000206)	(0.000144)
Ownership	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,924	11,747	41,924	11,747	41,924	9,527	53,671	53,671
R-squared	0.433	0.502	0.433	0.502	0.433	0.517	0.448	0.448

Notes: Standard errors in the parenthesis, clustered at province level.

iv. Placebo Tests

As is predicted by the model, a firm is going to learn from the best information source it can get, and thus I use the maximum of all destination GGI in my empirical study. As comparison, here I use the weighted average of all destination GGI, where the weight is the trade value. Based on the result, GGI is not significant no matter trading with more or less gender-equal cultures. This also gives extra credit to the previous results, and showed that the fact that the asymmetry of the results is not driven the sample size since here the sample size is more balance but GGI is not significant in either column.

Table 9: Placebo Results

	Female Fraction	
	More	Less
GGI	0.0515	0.0915
	(0.0499)	(0.0793)
GGI*Firm age	-0.00201***	-0.00315***
	(0.000266)	(0.000369)
Ownership	Yes	Yes
Industry Fixed	Yes	Yes
Province Fixed	Yes	Yes
Observations	30,160	23,511
R-squared	0.421	0.482

Notes: Robust standard errors in the parenthesis, clustered at province level.

V. Conclusion

In this paper, using Chinese customs data and firm level data in 2004, and by measuring gender equality using Gender Gap Index, I proved that firms trading with destinations with more gender equal culture would hire a higher fraction of female workers and enjoy higher profits. This is because firm learn about estimating female workers' productivity through international trade, and there would be information update only when Chinese firms trade with countries with better information about female workers. This transmission of culture is thus naturally asymmetric where there is no impact on firms which trading with less gender-equal cultures. Moreover, this alleviation of gender discrimination is more enjoyed by high skill female workers.

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VII. Appendix

A. 1. Conditions to guarantee the validity of hiring rules

Now we consider the restrictions the payoffs need to satisfy for firms to follow the rule that a worker is hired only when the signal is good. It must be that for a worker with good signal, the expected payoff is positive while for a worker with a bad signal, the expected payoff is negative.

$$\begin{aligned}&\text{expected payoff for hiring a female worker with good signal}\\&= prob(I_i = 1 \mid S_i = good) * \mu_q + prob(I_i = 0 \mid S_i = good) * \mu_n\\&= T\mu_q + (1-T)\mu_n > 0\end{aligned}$$

$$\begin{aligned}&\text{expected payoff for hiring a female worker with bad signal}\\&= prob(I_i = 1 \mid S_i = bad) * \mu_q + prob(I_i = 0 \mid S_i = bad) * \mu_n\\&= \frac{(1-P)q\mu_q + P(1-q)\mu_n}{(1-P)q + P(1-q)} < 0\end{aligned}$$

We therefore derive the condition for payoffs to let the firm fully trust the signal:

$$\begin{cases}\mu_q > \dfrac{1-T}{T}(-\mu_n) = \dfrac{(1-P)(1-q)}{Pq}(-\mu_n)\\[2ex] \mu_q < \dfrac{P(1-q)}{(1-P)q}(-\mu_n)\end{cases} \Rightarrow \frac{(1-P)(1-q)}{Pq}(-\mu_n) < \mu_q < \frac{P(1-q)}{(1-P)q}(-\mu_n)$$

For the condition to be meaningful, we need the upper limit to be larger than the lower limit:

$$\frac{(1-P)(1-q)}{Pq}(-\mu_n) < \frac{P(1-q)}{(1-P)q}(-\mu_n) \Rightarrow P > \frac{1}{2}$$

Therefore, the condition we derived above is plausible only when P is larger than a half, which is always satisfied as long as the signal is informative.

A.2. Taste-based discrimination model

Another commonly used model in discrimination is taste-based discrimination models. Under the same setup as in this paper, I briefly show here that a taste-based discrimination model would generate opposite predictions on profits compared to the statistical model I use in this paper.

If taste-based, then there is a distaste parameter α for female workers. Similarly, a firm only hires a female worker with good signal, but this requires that the distaste for female workers cannot be too large:

expected utility for hiring a female worker with good signal

$$= prob(I_i = 1 \mid S_i = good) * \mu_q + prob(I_i = 0 \mid S_i = good) * \mu_n - \alpha$$
$$= T\mu_q + (1-T)\mu_n - \alpha > 0$$

As long as the original α is not too large, female fraction within a firm takes the same function form as in statistical discrimination set-up with:

$$\frac{\partial L_m}{\partial \alpha} = 0, \ \frac{\partial L_f}{\partial \alpha} = 0, \ \frac{\partial T}{\partial \alpha} = 0$$

The wage paid to female workers, however, is lower than the statistical discrimination case:

$$w_f = \delta\left(T\mu_q + (1-T)\mu_n - \alpha\right)$$

Note that the distaste affects the employer's utility, but does not directly affect a firm's profit in monetary value. The expected profit a firm gets from a female worker is then:

expected profit from a female worker

$$= T\mu_q + (1-T)\mu_n - \delta\left(T\mu_q + (1-T)\mu_n - \alpha\right)$$
$$= (1-\delta)\left(T\mu_q + (1-T)\mu_n\right) + \delta\alpha$$

The profit of the firm is written as:

$$\pi = L_m(1-\delta)\mu_q + L_f\left((1-\delta)\left(T\mu_q + (1-T)\mu_n\right) + \delta\alpha\right)$$

Profit per worker is then:

$$U = \frac{\pi}{L_m + L_f} = \frac{L_m(1-\delta)\mu_q + L_f\left\{(1-\delta)\left(T\mu_q + (1-T)\mu_n\right) + \delta\alpha\right\}}{L_m + L_f}$$

As is mentioned above, when α is not large, the hiring decision is the same with change in the distaste parameter with $\partial L_m / \partial \alpha = 0, \ \partial L_f / \partial \alpha = 0, \ \partial T / \partial \alpha = 0$. Is it then obvious that profit per worker is increasing in α. As a result, when exporting to more gender-equal cultures with smaller α, firm earns lower profit per worker while when exporting to less gender-equal cultures with larger α, firm earns a higher profit per worker. Therefore, under the same set-up of the model, the change in profit per worker in the taste-based discrimination case is different from what would be predicted in the statistical discrimination case.

A. 3. Calculation of GGI (transaction frequency)

$$GGI_i = \max_c\{F(n_{ic}) * (GGI_c - GGI_{China}) + GGI_{China}\}$$

Where GGI_c is the GGI of origin/destination country c and GGI_{China} is the GGI value of China. Here n_c is the total number of transactions firm i has with country c, and $F(\cdot)$ is an increasing function of transaction number with the value of $F(\cdot)$ lying between 0 and 1. In my paper, for simplicity, I use the cumulative distribution function of normal distribution as $F(\cdot)$.

A. 4. Construction of Control Variables

A.4.1. Skill Ratio

Skill ratio is measured by number of high-skill workers over the total number of employees in a firm. A worker is identified as high-skill worker as long as he/she has a college degree, bachelor's degree, master's degree or above.

A.4.2. Output

Here I use log of output. Output is the monetary value of the total production of the firm, measured in 1000 RMBs.

A.4.3. Firm Age

Here I use the log of firm age, where firm age is the number of years a firm has operated. In Industrial Firm Database, the opening year of the firm is recorded. Since the main data I use in this paper is 2004, firm age thus equals to 2004 minus the opening year plus one.

A.3.4. Firm Size

Here I use log of firm size. Firm size is measured by the number of employees a firm hires at the end of a year.

A.4.5 Processing Trade

In customs data, it reports the trade mode for each transaction. Here processing trade is the fraction of trade value that belongs to processing trade for an exporter/importer in a year.

A.4.6. Ownership

Following Brandt et al. (2012), I classify firm into different ownership groups based on their registration type: state-owned, hybrid/collective, private, foreign, HMT, and others. The limited liability corporations and shareholding corporations are classified into one of the above groups based on their registered capital.

Table A1: Top 20 FDI source/export/import countries/regions

	FDI		Export		Import	
Rank	Country/region	percent	Country/region	percent	Country/region	percent
1	Hong Kong (China)	31.33	United States	21.06	Japan	16.80
2	Virgin Islands	11.10	Hong Kong (China)	17.01	Taiwan (China)	11.55
3	South Korea	10.30	Japan	12.38	South Korea	11.09
4	Japan	8.99	South Korea	4.68	United States	7.97
5	United States	6.50	Germany	4.01	Germany	6.92
6	Taiwan (China)	5.14	Netherlands	3.12	China	5.39
7	Cayman Islands	3.37	United Kingdom	2.53	Malaysia	3.25
8	Singapore	3.31	Taiwan (China)	2.27	Singapore	2.50
9	Samoa	1.86	Singapore	2.14	Russian Federation	2.16
10	Germany	1.75	France	1.67	Hong Kong (China)	2.10
11	Netherlands	1.34	Italy	1.55	Thailand	2.05
12	United Kingdom	1.31	Russian Federation	1.53	Australia	2.05
13	Australia	1.09	Australia	1.49	Philippines	1.62
14	France	1.08	Canada	1.37	Brazil	1.54
15	Canada	1.01	Malaysia	1.36	India	1.37
16	Mauritius	0.99	United Arab Emirates	1.15	France	1.37
17	Macao (China)	0.90	Indonesia	1.05	Saudi Arabia	1.34
18	Bermuda	0.70	India	1.00	Canada	1.31
19	Malaysia	0.64	Belgium	0.99	Indonesia	1.29
20	Italy	0.46	Thailand	0.98	Italy	1.15
Top 3	52.74		50.45		39.44	
Top 5	68.23		59.14		54.33	
Top 10	83.66		70.87		69.72	
Top 20	93.19		83.35		84.80	

Notes: FDI data comes from the China Statistical Yearbook published by National Bureau of Statistics in China at http://www.stats.gov.cn/. Export and import data is calculated based on customs data of China in 2004. For FDI, Virgin Islands (2), Cayman Islands (7), Samoa (9), Mauritius (16), Bermuda (18) are typical free ports in investments. Considering the real source of the investment from these countries/regions, then the FDI source countries might be even more concentrated than the data shows in the table. Another to note is that China is the fifth largest origin of its own import. This is because many firms try to benefit from the tax refund policy for export so there is a fairly high amount of re-import in China.

Table A2: Calculation of GGI and Four Sub-indexes

Sub-indexes	Ratios	Weights
Economic Participation and Opportunity	female labor force participation over male value	0.199
	wage equality between women and men for similar work (converted to female-over-male ratio)	0.310
	estimated female earned income over male value	0.221
	female legislators, senior officials, and managers over male value	0.149
	female professional and technical workers over male value	0.121
	Total	1
Educational Attainment	female literacy rate over male value	0.191
	female net primary level enrolment over male value	0.459
	female net secondary level enrolment over male value	0.230
	female gross tertiary level enrolment over male value	0.121
	Total	1
Health and Survival	female healthy life expectancy over male value	0.307
	sex ratio at birth (converted to female over male ratio)	0.693
	Total	1
Political Empowerment	women with seats in parliament over male value	0.310
	women at ministerial level over male value	0.247
	number of years of a female head of state (last 50 years) over male value	0.443
	Total	1

Table A3: Rank of All Countries by GGI

Rank	Country	Rank	Country	Rank	Country
1	Sweden	40	Thailand	79	Japan
2	Norway	41	Argentina	80	Gambia
3	Finland	42	Mongolia	81	Malawi
4	Iceland	43	Lesotho	82	Ecuador
5	Germany	44	Poland	83	Cyprus
6	Philippines	45	Trinidad and Tobago	84	Madagascar
7	New Zealand	46	Romania	85	Zambia
8	Denmark	47	Uganda	86	Kuwait
9	United Kingdom	48	Ukraine	87	Bolivia
10	Ireland	49	Russian Federation	88	Mauritius
11	Spain	50	Slovak Republic	89	Cambodia
12	Netherlands	51	Slovenia	90	Tunisia
13	Sri Lanka	52	Kyrgyz Republic	91	Bangladesh
14	Canada	53	Czech Republic	92	Korea, Rep.
15	Australia	54	Georgia	93	Jordan
16	Croatia	55	Hungary	94	Nigeria
17	Moldova	56	Luxembourg	95	Guatemala
18	South Africa	57	Venezuela	96	Angola
19	Latvia	58	Ghana	97	Algeria
20	Belgium	59	Dominican Republic	98	India
21	Lithuania	60	Peru.	99	Mali
22	Colombia	61	Albania	100	Ethiopia
23	United States	62	Nicaragua	101	United Arab Emirates
24	Tanzania	63	China	102	Bahrain
25	Jamaica	64	Paraguay	103	Cameroon
26	Switzerland	65	Singapore	104	Burkina Faso
27	Austria	66	Uruguay	105	Turkey
28	Macedonia	67	Brazil	106	Mauritania
29	Estonia	68	Indonesia	107	Morocco
30	Costa Rica	69	Greece	108	Iran
31	Panama	70	France	109	Egypt
32	Kazakhstan	71	Malta	110	Benin
33	Portugal	72	Malaysia	111	Nepal
34	Botswana	73	Kenya	112	Pakistan
35	Israel	74	Honduras	113	Chad
36	Uzbekistan	75	Mexico	114	Saudi Arabia
37	Bulgaria	76	Zimbabwe	115	Yemen
38	Namibia	77	Italy		
39	El Salvador	78	Chile		

Table A4: Sub-index

	Female Fraction			
	All	All	Only Better	Only Worse
GGI	0.0281*	0.0785***	0.0899***	0.0251
	(0.0170)	(0.0120)	(0.0260)	(0.0476)
GGI*Firm age	-0.00356***	-0.00208***	-0.00215***	-0.00247***
	(0.000271)	(0.000211)	(0.000214)	(0.000736)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes
Province Fixed	No	Yes	Yes	Yes
Observations	53,671	53,671	45,631	8,040
R-squared	0.212	0.448	0.437	0.516

Notes: Standard errors in the parenthesis, clustered at county level.

Table A5: Controlling for price

	Female Fraction			
	ln(price)		Relative Price	
	More	Less	More	Less
GGI	0.168***	0.0195	0.163***	-0.0379
	(0.0326)	(0.131)	(0.0328)	(0.129)
GGI*Firm age	-0.00192***	-0.00200***	-0.00209***	-0.00203***
	(0.000213)	(0.000637)	(0.000211)	(0.000643)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	45,701	7,970	45,701	7,970
R-squared	0.441	0.514	0.438	0.514

Notes: Standard errors in the parenthesis, clustered at county level.

Table A6: Profit (Impute 0.001)

	ln(Profit)			
	All	All	Only Better	Only Worse
GGI	4.546***	3.657***	6.389***	3.145
	(0.679)	(0.631)	(1.052)	(4.364)
GGI*Firm age	-0.199***	-0.193***	-0.198***	-0.235***
	(0.0116)	(0.0115)	(0.0124)	(0.0285)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes
Province Fixed	No	Yes	Yes	Yes
Observations	52,951	52,951	45,063	7,888
R-squared	0.091	0.111	0.120	0.071

Notes: Standard errors in the parenthesis, clustered at county level.

Table A7: Profit (Add a constant)

	ln(Profit)			
	All	All	Only Better	Only Worse
GGI	0.00253	0.00385*	0.0124**	0.00107
	(0.00351)	(0.00225)	(0.00527)	(0.00188)
GGI*Firm age	-2.11e-05	-3.12e-05	-4.21e-05	-5.96e-05
	(5.55e-05)	(4.38e-05)	(4.78e-05)	(4.22e-05)
Ownership	Yes	Yes	Yes	Yes
Industry Fixed	No	Yes	Yes	Yes
Province Fixed	No	Yes	Yes	Yes
Observations	52,950	52,950	45,062	7,888
R-squared	0.043	0.064	0.076	0.658

Notes: Standard errors in the parenthesis, clustered at county level.