

Gender Discrimination and Firm Profit Efficiency: Evidence from Brazil*

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Abstract

In this study, we investigated discrimination against women within the Brazilian labor market using firm-level data. We based on employer discrimination model proposed by Becker and considering the proportion of female employees as a proxy for the extent of discrimination. Estimating the profit efficiency of firms using data envelopment analysis, and regressing it on the proportion of female employees and other firm characteristics, we found that the proportion of female employees has positive effect on firm profit efficiency. Our finding provided strong evidence of the existence of discrimination against female employees within the Brazilian labor market.

Keywords: Latin America, Brazil, gender discrimination, DEA

*The authors thank Valentin Zelenyuk for helpful comments and providing his Matlab code for DEA. This work was supported by Grants-in-Aid for Scientific Research (No.21730228).

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1 Introduction

It is well known that income distribution in Brazil is extremely unequal. According to the United Nations Development Program (UNDP, 2006), the top 20% of the Brazilian population earns an income that is 26 times larger than that earned by the bottom 20%, yielding a Gini coefficient of 0.58. Despite this fact, many argue that discrimination does not exist in Brazil, particularly discrimination against racial minorities. However, recent research suggests that there indeed exists discrimination against racial minorities and women in Brazil.

Discrimination within any society can lead to the distortion of resource allocation, and may discourage economic growth. No less an authority than the World Bank (2001) claims that gender inequality disadvantages not only women but also the entire society, while hindering economic development, particularly in low-income countries.

Discrimination against women takes on numerous forms and exists in all sectors of society, including the labor market. Regarding the causes of discrimination, inequality of educational opportunity is considered the root cause of many other forms of inequality. In most countries, especially in developing countries, limitations on women's access to education and inequality in education are the root causes of many aspects of gender inequality.

Despite this fact, the educational attainment of women in Brazil and several other Latin American countries is currently higher than that of men. In one study, the Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira/Ministério da Educação (Inep/MEC, 2004) found that in

2001, Brazilian women had attained an average of 6.2 years of education whereas Brazilian men had attained an average of 5.9 years. Despite women's higher educational attainment, discrimination exists within the Brazilian labor market, a discrepancy that we investigated in this study.

The majority of the previous research on gender discrimination in Brazil estimated the wage functions for men and women separately and considered the difference between the coefficients as a measurement of discrimination. However, these estimated coefficients reflected the bias that inevitably arises due to the existence of unobservable factors that affect productivity. If such unobservable factors systematically differ according to gender, the variable of "discrimination" as measured by this method would be little more than a measure of the gender difference in productivity. To address this concern, we employed an approach that differed from that of previous research to determine whether discrimination exists within the Brazilian labor market. Specifically, we assumed that if female employees are paid less than their productivity warrants due to the existence of discrimination, firms can increase their profitability by employing more women. Based on this assumption, we employed data envelopment analysis (DEA) to analyze the relationship between the proportion of female employees employed by a firm and the firm's profit efficiency to test for the existence of discrimination.

The remainder of this paper is organized as follows. Section 2 reviews the literature regarding gender discrimination while section 3 discusses the theoretical background. Next, section 4 describes the empirical strategy that we employed, and section 5 describes the data and the variables that

we examined and our justification for doing so. Section 6 discusses our results before closing the study with concluding remarks.

2 Literature Review

Much research into male-female wage discrimination has been conducted using the human capital approach. According to this approach, discrimination against women is considered to exist whenever the relative wage of men exceeds the relative wage that would have prevailed if men and women had been paid equally according to the same criteria (Oaxaca, 1973), with the market discrimination coefficient being defined as the percentage wage differential between two types of perfectly substitutable labor (Becker, 1971). Blinder (1973) and Oaxaca (1973) developed a simple means of decomposing wage differentials into the proportion of the differential arising from differences in productivity and discrimination. To perform Blinder-Oaxaca decomposition, suppose that the wages of each male and female employee are determined by the following human capital earnings equations:

$$\ln w^m = X^m \beta^m + u^m, \quad (1)$$

$$\ln w^f = X^f \beta^f + u^f. \quad (2)$$

Here, w denotes the wage, X denotes the vector of the labor characteristics affecting productivity, β the vector of the coefficients of earnings functions, and u the error term. The superscripts “ m ” and “ f ” denote male and female, respectively. By estimating β^m and β^f by the ordinal least square

using individual-level data and defining the estimated vectors of coefficients as $\hat{\beta}^m$ and $\hat{\beta}^f$, we can decompose the wage differentials as follows:

$$\overline{\ln w^m} - \overline{\ln w^f} = \bar{X}^m \hat{\beta}^m - \bar{X}^f \hat{\beta}^f = (\bar{X}^m - \bar{X}^f) \hat{\beta}^m + \bar{X}^f (\hat{\beta}^m - \hat{\beta}^f). \quad (3)$$

Here, $\overline{\ln w}$ denotes the average of the log wage and \bar{X} the vector of the average value of the characteristics affecting productivity. The first term on the right side of the equation can be interpreted as the wage differential because of the difference in productivity between men and women and the second term as the wage differential not explained by the difference in productivity, i.e., discrimination.

Blinder-Oaxaca decomposition has been employed in many studies on discrimination¹. Focusing on the Brazilian labor market, Lovell (2000) estimated the monthly wages of white, black, and mixed-race women and men working in the states of São Paulo and Bahia using a sample of 1991 census data. She found that discrimination did indeed exist in Brazilian labor market, with women and blacks working in São Paulo experiencing greater discrimination compared to their counterparts in Bahia, but that occupational and wage distributions were more equal in São Paulo. Using data collected by the National Household Survey (PNAD) of 1992 and 1998, Loureiro, Carneiro and Sachsida (2004) also tested for the existence of racial and gender discrimination, accounting for sample selection bias by simultaneously estimating the labor market participation function and the wage function following Heckman (1979). Even after controlling for sam-

ple selection bias, they found that more than 50% of the male-female wage differential could be attributed to discrimination, with the discrimination differential being larger in urban areas.

In this study, we faced several limitations in using Blinder-Oaxaca decomposition to measure discrimination. First, we were unable to distinguish between discrimination due to unequal pay for equal work and discrimination due to unequal occupational distribution, i.e., occupational segregation. Several researchers have addressed this challenge. When Birdsall and Fox (1985) analyzed the male-female wage differential of primary and secondary Brazilian school teachers, they found evidence of only a low level of occupational segregation, and that the opportunity to be promoted to a secondary school position, which paid a higher salary than did a primary school position, was relatively equal for men and women when the differences between the observable characteristics of male and female teachers were taken into account. When Nomura (2010) followed Brown, Moon and Zoloth (1980) by including more comprehensive occupations in his analysis, he found that wage discrimination for the same position was greater than was occupational segregation; this was consistent with the findings of Birdsall and Fox (1985).

A second limitation that we faced was the possible existence of unobservable factors affecting productivity that systematically differ according to gender. Although Griliches (1977) and Card (1999) demonstrated that the impact of unobservable factors on wages was limited, the measurements of discrimination using wage regression could have led them to overestimate the extent of discrimination. To address this problem, Hellerstein, Neumark

and Troske (2002) tested the discrimination hypothesis of Becker (1971) more directly by using a “market testing” approach. Analyzing U.S. firm-level data, they found a positive correlation between profitability and the proportion of female workers in the workforce. Since firms can earn more profit by employing more women when women are paid less than their productivity warrants, Hellerstein et al. (2002) considered the existence of this correlation as evidence of gender discrimination. When Kawaguchi (2007) performed market testing using Japanese firm-level panel data while maintaining a strong focus on unobservable productivity shocks, he identified the existence of a positive correlation between female employment and firm profitability within the Japanese labor market. Since the costs of gender discrimination and inequality are larger in less developed countries (World Bank, 2001), market testing should be performed using data from developing countries as well. Nevertheless, no study before the present one has performed market testing using Brazilian firm-level data.

This study, therefore, addressed a research gap by examining the relationship between the proportion of female employees and firm profit efficiency using Brazilian firm-level data to test the discrimination hypothesis proposed by Becker (1971). Although our research generally accords with that of Hellerstein et al. (2002) and Kawaguchi (2007), we defined profit efficiency as the distance from an actual point to the frontier identified by non-parametric estimation, i.e., the DEA, and focused on estimating loss in efficiency due to gender discrimination.

3 Theoretical Background

We based our method on the employer discrimination model proposed by Becker (1971), who assumed that an employer working for a firm prefers to maximize his or her utility instead of the firm's profit taking wage as given.

Consider that a firm can produce an output Y using the inputs of male labor M , female labor F , and other inputs $OI = (OI_1, \dots, OI_{J-2})$. The utility function of an employer who prefers not to employ female workers and thus pays a psychic cost when forced to employ women can be defined as

$$U = pY - w_M M - w_F F - d \left(\frac{F}{M + F} \right) - w_{OI} OI, \quad (4)$$

where p is the price of the output; w_M and w_F are the wages of male and female employees, respectively; w_{OI} is the price of other inputs; and d is the discrimination coefficient representing the extent of the employer's discrimination against women, which we assumed to vary across firms.

The employer's utility maximization is given by

$$MRP_M + \frac{dF}{(M + F)^2} = w_M, \quad (5)$$

$$MRP_F - \frac{dM}{(M + F)^2} = w_F, \quad (6)$$

where MRP_M and MRP_F are the marginal revenue products of male and female workers, respectively. The marginal revenue product of female workers is set above their wages while that of male workers is set below their

wage. Thus, only firms whose employers do not engage in discrimination ($d = 0$) can maximize their profit, and the profit decreases with an increase in d .

To investigate the existence of discrimination against female workers in the Brazilian labor market, we employed a profit efficiency model following Färe and Grosskopf (2004). The profit efficiency model begins with defining the notation of technology set T as

$$T = \{(X, Y) : X \text{ can produce } Y\}, \quad (7)$$

where $X = (M, F, OI) \in \mathfrak{R}_+^J$ is a nonnegative vector of inputs including labor, $Y \in \mathfrak{R}_+^G$ is a non-negative vector of outputs. Given output prices $p \in \mathfrak{R}_+^G$ and input prices $w = (w_M, w_F, w_{OI}) \in \mathfrak{R}_+^J$, the maximum profit for a firm can be defined as

$$\Pi(p, w) = \sup \{pY - wX : (X, Y) \in T\}. \quad (8)$$

The boundary of T is referred to as the technology or the production frontier. The distance from the actual point of each firm in the production set T to the frontier of T , which is considered as its level of inefficiency, is determined by the firm's environmental variables $Z = (Z_1, \dots, Z_Q) \in \mathfrak{R}_+^Q$. Depending on their specific environment, firms may operate along the production frontier or at a point within the interior of their production frontier, with the former being considered as efficient firms and the latter

being considered as inefficient firms.

The Nerlovian profit efficiency is defined as

$$PE(p, w, Y, X; g_Y, g_X) = \frac{\Pi(p, w) - (pY - wX)}{pg_Y + wg_X}, \quad (9)$$

where g_X and g_Y are the directional vectors in which efficiency is evaluated.

This type of profit efficiency is often regarded as aggregate efficiency as it encompasses two types of efficiency: technical and allocative.

Under the condition that the output prices, wages, and efficiency directional vectors are identical across firms, the profit efficiency of firms can be estimated by examining their input and output values. Recognizing that the profit efficiency of firms is determined by their specific characteristics, we estimated the impact of firm-specific characteristics on efficiency. Among the many factors that likely impact profit efficiency, we examined the impact of discrimination against women using the proportion of female employees as a proxy for the extent to which an employer engages in discrimination. Since seeking to fulfill the goal of profit maximization is a necessary condition for achieving profit efficiency, only firms whose hiring managers do not engage in discrimination against women can attain profit efficiency. That is, assuming the existence of discrimination, a firm with a high proportion of female workers will have a higher level of profit efficiency than will a firm employing a low proportion of female workers.

4 Empirical Strategy

Our empirical procedure follows Simar and Wilson (2000) and Zelenyuk and Zheka (2006) and consists of two stages. In the first stage, we estimate the profit efficiency of each firm by using DEA. Then in the second stage, we analyze the determinant of firm efficiency by regressing the profit efficiency obtained in the first stage on firm's characteristics.

4.1 Profit Efficiency Estimation

One challenge of researching profit efficiency is that data regarding output and input prices are usually unavailable as financial information (e.g., labor, material, and energy costs) is typically reported at the firm level. To overcome this challenge, we employed an alternative DEA approach to measure profit efficiency using financial information. Specifically, we used input and output data aggregated with price data in the traditional DEA model to measure a proxy for profit efficiency that encompassed both technical and allocative efficiency².

To measure such profit efficiency, we employ the cost and revenue-based efficiency index developed by Farrell (1957), which is defined as

$$PE_i \equiv \max_{\theta} \left\{ \theta \mid (x_i, \theta y_i) \in T \right\}, \quad (10)$$

where $x_i = wX_i$ is a vector of aggregated inputs and $y_i = pY_i$ is a vector of aggregated outputs. When $PE_i = 1$, the firm is considered to be efficient. And when $PE_i > 1$, the firm is considered to be inefficient, and the reciprocal

of PE_i , $0 < (1/PE_i) \leq 1$, represents the percent level of the efficiency of firm i relative to the production frontier.

Since the true technology sets cannot be directly observed, we employed the most common DEA procedure to estimate the best-practice frontier from the observed input-output combinations (x_i, y_i) , which is defined as

$$\hat{T} = \left\{ (x, y) \left| \begin{array}{l} y_g \leq \sum_{i=1}^n q_i y_{gi}, \quad g = 1, \dots, G, \\ x_j \geq \sum_{i=1}^n q_i x_{ji} \quad j = 1, \dots, J, \\ \sum_{i=1}^n q_i = 1, \quad q_i \geq 0, \quad i = 1, \dots, n, \end{array} \right. \right\}, \quad (11)$$

where \hat{T} is the DEA estimate of the true production frontier of T and q_i are the intensity variables over which optimization is made. By employing this procedure, the DEA estimate of individual efficiency at any point (x_i, y_i) can be obtained by replacing T with \hat{T} in (10) and solving the following linear programming problem:

$$\widehat{PE}_i = \max_{\theta, q_1, \dots, q_n} \left\{ \theta \mid (x_i, \theta y_i) \in \hat{T} \right\}. \quad (12)$$

It is clear that $\hat{T} \subseteq T$, therefore \widehat{PE}_i is downward-biased estimator of PE_i . To address this problem, we employ a bootstrap DEA procedure developed by several DEA researchers (e.g. Simar and Wilson, 2000; Henderson and Zelenyuk, 2007; Simar and Zelenyuk, 2007).

4.2 Determinants of profit efficiency

To investigate the dependency of firm efficiency on firm environmental variables, we regressed the profit efficiency gained from the first stage on several environmental variables. The determinant model of efficiency is expressed as

$$\begin{aligned}\widehat{PE}_i &= Z_i\beta + \varepsilon_i \\ &= \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \beta_3 Z_{3i} + \beta_4 Z_{4i} + \text{ind}_i\beta_5 + v_i + \varepsilon_i, \quad (13)\end{aligned}$$

where \widehat{PE}_i is the profit efficiency of i th firm as defined in (12); β is a vector of the parameters that are being estimated; Z_i is a vector of firm environmental variables that may affect the efficiency of the i th firm. Z_{1i} is the proportion of female employees compared to total employees. If workplace discrimination against women existed, then employing a higher proportion of female workers would result in higher profit efficiency. Thus, a negative β_1 would lead to rejection of the null hypothesis that there is no gender discrimination³. The variable of firm age, Z_{2i} , may or may not have positive effect on firm performance; whereas firms tend to perform functions more effectively, which increases performance, with the experience that only can be acquired with increased age, their level of bureaucracy (organizational rigidity), which leads to increases in variable costs and overhead expenses, and thereby decreases in performance, also increases with age. Z_{3i} is an output variable (the logarithm of total sales) that captures the scale effect. To account for the opportunity cost of capital, we included the ratio of

fixed assets to total sales, Z_{4i} , in the equation. We also introduced industry dummies, ind_i , to control industrial heterogeneity; a proxy, v_i , to capture productivity or demand shocks; the idiosyncratic error term, ε_i . With regard to the proxy, v_i , we employed the approach used by Kawaguchi (2007) to control productivity or demand shocks, which he based on consideration of two types of proxy variables: one is investment following Olley and Pakes (1996) and the other is intermediate inputs following Levinsohn and Petrin (2003).

Assuming that current positive productivity shocks will affect a firm's future level of investment, Olley and Pakes (1996) suggested that a firm's level of investment can be used as a proxy of unobserved productivity shocks in the production function. When, according to their suggestion, the investment function is expressed as $I_i = I(k_i, v_i)$ and it is assumed that $\partial I_i / \partial v_i > 0$, where I_i is the amount of investment, k_i is the capital stock, and v_i is the productivity shock, productivity shock can be expressed as an inverse function of investment and capital. Following Kawaguchi (2007), we specified the function as

$$v_i = g(I_i, k_i) = \lambda_1 \frac{I_i}{k_i} + \lambda_2 \left(\frac{I_i}{k_i} - \frac{\bar{I}_i}{\bar{k}_i} \right)^2. \quad (14)$$

At this point, we omitted from our sample those firms whose micro-level data indicated that they made no investments. Levinsohn and Petrin (2003) suggested using intermediate inputs as a proxy variable for productivity shocks to avoid omitting firms without reporting investments, explaining

that if the demand function of intermediate inputs is expressed as $m_i = m(v_i, k_i)$, productivity shock can be expressed as a function of intermediate inputs and capital stock. Again following Kawaguchi (2007), we specified the function as

$$v_i = h(m_i, k_i) = \delta_1 \frac{m_i}{C_i} + \delta_2 \left(\frac{m_i}{C_i} - \frac{\overline{m_i}}{C_i} \right)^2 + \delta_3 \left(\frac{m_i}{C_i} - \frac{\overline{m_i}}{C_i} \right) \times \frac{k_i}{y_i}, \quad (15)$$

where C_i is the total production cost, m_i is the cost of intermediate inputs, and k_i/y_i is the asset-to-sales ratio.

Traditional two-stage DEA models typically employ OLS or the Tobit model to estimate (13). However, Simar and Wilson (2007) argued that standard DEA efficiency estimates are inappropriate because they do not provide a coherent description of a data-generating process and because they are serially correlated. Recognizing that the DEA estimation obtained using the traditional two-stage model is inconsistent in the second-stage regression, they proposed the use of a two-stage bootstrap DEA approach to obtain a consistent result. In this study, our use of one of their bootstrap procedures, Algorithm 2⁴, allowed us to replace the unobserved PE_i by its bias-corrected estimate, \widehat{PE}_i^{bc} . In this procedure, \widehat{PE}_i^{bc} is defined to be equal or greater than one, the distribution of ε_i is restricted by the condition $\varepsilon_i \geq 1 - Z_i\beta$, and the efficiency determinant model can be written as

$$\widehat{PE}_i^{bc} \approx Z_i\beta + \varepsilon_i, \quad (16)$$

where

$$\varepsilon_i \sim N(0, \sigma_\varepsilon^2), \quad \text{such that } \varepsilon_i \geq 1 - Z_i\beta. \quad (17)$$

5 Data

We obtained the data that we analyzed in this paper from the World Bank Investment Climate Survey, which used standardized survey instruments and a uniform sampling methodology to analyze firm performance and the business environment of developing countries⁵. To conduct a survey on Brazil, the Investment Climate Survey Group of the World Bank randomly sampled 1,641 firms from nine manufacturing industries in 13 geographic regions in the reference year 2002. After excluding observations with missing values, our working sample consisted of 1,456 firms.

We used the variable of the value of total sales as the output and the variables of labor, material, and energy costs as the inputs to estimate the profit efficiency score of each firm using a bootstrap DEA procedure. We defined the labor cost as the total annual cost of paying wages, salaries, bonuses, and social security payments to employees; material cost as the total annual cost of raw materials and intermediate goods used in production; and energy cost as the total annual costs of fuel and electricity.

Such measurement of output and inputs enables us to extend the interpretation of technology to encompass more than simply engineering capacity, and gives us some justification for pooling data over sub-industries to mea-

sure efficiency of each firm using DEA (Zelenyuk and Zheka, 2006, p148).

A benefit of pooling data over sub-industry was that it allowed us to increase the sample size, which would prove to be very important in obtaining an estimation for the efficiency determinant model in the second stage of this study⁶. Recognizing this benefit, we pooled all the data collected from firms within various sub-industries in manufacturing and estimated the meta-frontier of the entire manufacturing industry.

The descriptive statistics of our dataset are presented in Table 1.

[Table 1 is inserted here]

6 Empirical Results

6.1 Estimation of profit efficiency

In the first stage, we obtained the profit efficiency score of each firm by solving the linear programming problem presented in Equation (10). When we then used the kernel density estimator to obtain the density of the efficiency scores in order to identify any outliers, our results suggested the existence of several outliers in the sample. Zelenyuk and Zheka (2006) suggested that there are mainly three reasons can give rise to efficiency outliers. First, firms with efficiency outliers follow a different distribution of efficiency; namely, these firms operate under a different production frontier. Second, although all firms follow the same distribution pattern, experiencing external shocks (e.g., strikes or unexpected incidents) cause some firms to appear far within the tail of the distribution. Finally, when firms commit errors when record-

ing data regarding their output or input variables, such as by inserting extra digits, their efficiency scores will be incorrect. We believe that outliers may have arisen in our sample due to the last two factors, as the output and input data for several firms appeared unusual. As these outliers could disturb our estimation of the frontier, we omitted 2.5% of the firms on both sides of the efficiency density distribution (5% of firms in total) from our sample.

We recognized that although our revised sample contained a distribution of efficiency scores that presented us with desirable properties for analysis, it may not have been representative of the original sample. Fortunately, we found that we could use the Simar-Zelenyuk adaption of the Li Test (Simar and Zelenyuk, 2007) to address this problem. We obtained a bootstrap P-value of 0.929 using the Simar-Zelenyuk-adapted Li Test and, thus, could not reject the hypothesis that the distributions of the original and revised samples are equal. Therefore, we used the revised sample in our two-step estimations.

Examining the bootstrap bias-corrected efficiency scores that we had obtained during the first stage, we found that the aggregate of the efficiencies obtained by our bootstrap bias-corrected estimation was larger than that obtained by our original DEA estimation. Our result is thus consistent with the bootstrap DEA literature, which asserts that the original DEA estimates are biased downward.

6.2 Determinants of efficiency

In the second stage, we estimated the efficiency determinant model. We obtain parameters and the confidence intervals from performing 2,000 replications of the bootstrapping procedures. Specifically, we regressed the bias-corrected efficiency scores that we obtained from the first stage on firm environmental variables and industry dummies using Algorithm 2 of Simar and Wilson (2007) and performed 2,000 replications of the bootstrapping procedures to both ensure bias correction and obtain the confidence intervals of the estimated coefficients. Our results are presented in Table 2.

[Table 2 is inserted here]

As shown in Column (1), which reports the basic estimation result, the coefficient of the proportion of female employees is negative and statistically significant at the 1% level according to the bootstrap confidence intervals, as we had expected. The negative coefficient of the proportion of female employees suggests that a proportion of female workers has a positive effect on firm profit efficiency, and thus provides strong evidence for the existence of gender discrimination.

In creating Column (2), which reports the result of the estimation using Olley and Pakes (1996) proxy variables for productivity or demand shocks, we omitted several observations from the sample shown in Column (1) because of the unavailability of investment data. As can be observed, the coefficients are statistically significant, and suggest that investment captures productivity or demand shocks. Nevertheless, the coefficient of the proportion of female employees did not change significantly after the proxy

variables were included in the model.

As shown in Column (3), which reports the result of the estimation including Levinsohn and Petrin (2003) proxy variables for productivity or demand shocks, the coefficients are also statistically significant. However, when we used intermediate inputs as proxies, we found that the coefficient of the proportion of female employees increased, a result that was contrary to our expectation that the coefficient of the proportion of female employees would be upward biased⁷.

Our finding that the logarithm of total sales has positive effect on firm profit efficiency in all specifications suggests that larger firms tend to be more efficient than smaller firms within the Brazilian manufacturing industry. In contrast, we found that the ratio of fixed assets to total sales has negative effect on firm profit efficiency in all specifications. Somewhat surprisingly, we also found that firm age has negative effect on firm profit efficiency in all specifications. As discussed in Section 3, firm age may have positive effect on firm performance (greater age brings with it greater knowledge) or negative effect (greater age brings with it greater organizational rigidity). We, therefore, interpreted our finding as the latter factor having a greater impact on firm performance than the former factor does.

6.3 Proportion of female employees and total cost

If female employees are paid a lower wage than male employees due to the existence of workplace discrimination, a firm can achieve higher allocative efficiency by substituting male labor with female labor to decrease the labor

cost. As discussed in the previous section, the profit (aggregate) efficiency of a firm can be decomposed into two forms of efficiency: technical and allocative. However, performing this decomposition empirically requires access to data regarding the prices of output and input that are typically unavailable. Although it is difficult to decompose the profit efficiency into technical and allocative efficiency, it is worth to confirm whether higher female proportion leads to lower labor cost.

Following Kawaguchi (2007), we employed a total wage function to test the hypothesis that employing a higher proportion of female employees leads to lower labor cost. The total wage function is defined as

$$\log(wage_i) = \gamma_0 + \gamma_1 Z_{1i} + \gamma_2 \log(output)_i + \gamma_3 ind_i + u_i, \quad (18)$$

where $wage_i$ is the total labor cost of a firm and Z_{1i} is the proportion of female employees to total employees. If female employees are paid a lower wage than male employees due to the existence of workplace discrimination, the proportion of female employees would have negative effect on labor cost, given the same level of output. We estimated (18) by the ordinary least square and tested the null hypothesis $\gamma_1 = 0$ against the alternative hypothesis $\gamma_1 < 0$.

[Table 3 is inserted here]

As shown in Table 3, we found the coefficient of the proportion of female employees to be negative and significant at the 5% level, suggesting that employing a higher proportion of female employees within the Brazil-

ian manufacturing industry leads to a lower labor cost. Therefore, we can conclude that employing a higher proportion of female employees leads to higher allocative efficiency.

6.4 Robustness checks

As a robustness check, we also regressed profitability on the proportion of female employees following Hellerstein et al. (2002) and Kawaguchi (2007). In parallel with (12), the specification is as follows:

$$profitability_i = \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \beta_3 Z_{3i} + \beta_4 Z_{4i} + ind_i \beta_5 + v_i + \varepsilon_i, \quad (19)$$

where $profitability_i$ is defined as the ratio of total profit (total sales - total cost) to total sales and the explanatory variables on the right side are defined in the same manner as they are in (12).

The results of regression by the ordinal least square are reported in Table 4, with the results of the basic estimation for (19) in Column (1) and the results of the estimation using Olley and Pakes (1996) and Levinsohn and Petrin (2003) proxy variables for demand and productivity shocks in Columns (2) and (3), respectively.

[Table 4 is inserted here]

As shown in Column(1), we found that the proportion of female employees has positive effect on profitability, which supports the results that we obtained from the profit efficiency model and provides further evidence that gender discrimination exists within the Brazilian labor market.

As shown in Column (2), which reports the results when Olley and Pakes (1996) proxy variables are included in the regression, the coefficient of the proportion of female employees becomes more significant when these variables are included, although the coefficients of the proxy variables are insignificant. As shown in Column (3), which reports the result of the estimation including Levinsohn and Petrin (2003) proxy variables for demand and productivity shocks, the coefficients of the proxy variables are significant. Particularly noteworthy is that adding the proxy variables led the coefficient of the proportion of female employees to decrease, a result that contrasts with that obtained when using profit efficiency determinant models.

Consistent with the results obtained using profit efficiency determinant models, we found that firm size has positive effect on profitability in all specifications. In contrast with the results obtained using profit efficiency determinant models, we found that firm age and the ratio of fixed assets to total sales have no significant effect on firm profit ratio.

As each specification resulted in different conclusions, our results are not very reliable, one reason for which may be the quality of the data, as the survey data that we used contained missing values or outliers. Although we did our best to address these problems, we acknowledge the possibility that our use of these data skewed our estimations. Despite this caveat, we found that the proportion of female employees has positive effect on profit efficiency and profitability, regardless of the method or specification used to examine this effect, a finding that provides strong evidence of the existence of gender discrimination within the Brazilian labor market.

7 Conclusion

In this paper, we investigated gender discrimination in Brazil by employing a two-stage bootstrap DEA approach to profit efficiency, and testing the implication of the employer discrimination model proposed by Becker (1971). Our results indicate that the proportion of female employees has positive effect on firm profit efficiency, a finding that we found to be robust when we used several different methods and specifications. We consider this finding to be strong evidence of the existence of discrimination against female employees within the Brazilian labor market. Although we were unable to decompose aggregated profit efficiency into its components of technical efficiency and allocative efficiency, the results of our estimation of the total wage function indicate that a firm employing a high proportion of female workers incurs a lower labor cost while producing the same level of output compared with a firm employing a low proportion of female employees. Our findings support those reported in previous studies (e.g, Lovell, 2000; Loureiro et al., 2004; Nomura, 2010) that estimated workplace gender discrimination using Blinder-Oaxaca decomposition and that assumed that the male-female wage differential which could not be explained by differences in individual characteristics was due to discrimination.

Brazil has recently experienced very rapid economic growth, especially after the implementation of the Real Plan in 1994. Nevertheless, income inequality remains a serious concern, one that has been attributed to discrimination against women and racial minorities. As such, discrimination impedes fair competition and confounds equality of opportunities and out-

comes, it likely distorts resource allocation and hinders economic growth, negatively impacting not only women and discriminatory employers but also Brazilian society as a whole.

The results of our analysis indicate that employer discrimination against female employees leads to a loss of profit efficiency. A serious concern remaining is to estimate the loss. We plan to address this concern, as well as identify the ultimate bearers of discrimination, in our future research.

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Notes

¹See Altonji and Blank (1999) for more details.

²Färe and Grosskopf (1985), Färe and Zelenyuk (2002), and Färe and Grosskopf (2004) have theoretically discussed aggregated inputs or outputs in DEA model. There are also many empirical studies using aggregated inputs and outputs in DEA formulation. See the discussion in Zelenyuk and Zheka (2006).

³Note that a larger efficiency score means larger inefficiency. Therefore, the negative coefficients in the regressions mean the positive effect on firm efficiency.

⁴See Simar and Wilson (2007, p.42) for details.

⁵For more information about the survey, see <http://www.enterprisesurveys.org>

⁶Simar and Wilson (2007) argued that maximum likelihood often produces biased estimates in small samples. Therefore, a large sample size is preferred in the two-stage bootstrap DEA estimation.

⁷The same result is obtained in Kawaguchi (2007). Nevertheless, it is difficult to interpret these results.

Table 1

Discriptive statistics of study dataset

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Profit ratio (%)	28.62	22.51	-65.20	93.23
Log(wage)	9.02	0.92	4.80	15.45
Output variable (in thousands of R\$):				
Total sales	24700.00	134000.00	33.95	3670000.00
Input variables (in thousands of R\$):				
Labor cost	2490.78	10700.00	8.81	189000.00
Material cost	12300.00	73200.00	2.28	2110000.00
Energy cost	561.54	3941.27	0.01	90000.00
Explanatory variables:				
Proportion of female employees	0.37	0.30	0.36	0.30
Firm age	19.72	17.34	22.28	16.97
Fixed assets/Total sales	0.44	4.88	0.83	5.94
Investment/Fixed assets	0.74	5.27	1.96	21.26
Material cost/Total cost	0.62	0.21	0.58	0.19
Number of firms	1456			

Note: The number of observations of Investment/Fixed assets was 1338.

Table 2

Estimation results of the efficiency determinant model

	(1)	(2)	(3)
Constant	12.960	12.891	13.994
Proportion of female employees	-0.211	-0.211	-0.318
Firm age	0.017	0.015	0.007
Log(output)	-0.634	-0.629	-0.387
Fixed assets/Total sales	0.009	0.008	0.002
Investment/Fixed assets		-0.022	
$(I/FA - \text{mean}(I/FA))^2/1000$		0.306	
Material cost/Total cost			-4.919
$(MC/TC - \text{mean}(MC/TC))^2$			-19.839
$(MC/TC - \text{mean}(MC/TC)) * (FA/TS)$			0.079
Industry dummies	yes	yes	yes
σ	1.599	1.603	1.439
Number of observations	1456	1338	1456

Notes:

1. Estimation according to Algorithm 2 of Simar and Wilson (2007), with 2000 bootstrap replication to correct bias and obtain confidence intervals of the estimated regression coefficients.
2. The dependent variable was the bootstrap bias-corrected DEA estimate of the efficiency score.
3. All the coefficients were statistically significant at 0.01 significance levels, according to the bootstrap confidence intervals.

Table 3

Determinantion of total wage

Constant	4.952*** (0.181)
Proportion of female employees	-0.228** (0.100)
Log(output)	0.258*** (0.010)
Industry dummies	Yes
R ²	0.467
Number of observations	1456

Notes:

1. Standard errors in parenthesis.
2. ***, **, * represent 1%, 5%, 10% significance respectively.

Table 4

Estimation results of the profit determinant model

	(1)	(2)	(3)
Constant	-34.871*** (5.764)	-34.150*** (6.051)	-37.514*** (5.745)
Proportion of female employee	5.286* (3.139)	6.523** (3.320)	4.264 (3.124)
Firm age	0.026 (0.035)	0.049 (0.037)	0.019 (0.036)
Log(output)	3.890*** (0.339)	3.747*** (0.355)	4.346*** (0.385)
Fixed assets/Total sales	-0.072 (0.115)	-0.069 (0.115)	-0.045 (0.132)
Investment/Fixed assets		0.201 (0.319)	
$(I/FA - \text{mean}(I/FA))^2/1000$		-3.046 (3.370)	
Material cost/Total cost			-8.590*** (3.302)
$(MC/TC - \text{mean}(MC/TC))^2$			34.483*** (11.011)
$(MC/TC - \text{mean}(MC/TC)) * (FA/TS)$			-0.351 (0.993)
Industry dummies	yes	yes	yes
R ²	0.108	0.107	0.124
Number of observations	1456	1338	1456

Notes:

1. Standard errors in parenthesis.

2. ***, **, * represent 1%, 5%, 10% significance respectively.