The Developing Economies

The Developing Economies 57, no. 1 (March 2019): 55–82

REGIONAL DIFFERENCES IN THE GENDER EARNINGS GAP IN BRAZIL: DEVELOPMENT, DISCRIMINATION, AND INEQUALITY

Silvio Hong Tiing TAI[1,2]* and Izete Pengo BAGOLIN[2]

[1]*RITM, Paris-Sud University, Orsay, France; and* [2]*PUCRS, Business School, Porto Alegre, Brazil*

First version received May 2017; final version accepted July 2018

This paper studies the decomposition of the gender earnings gap in the Brazilian labor market using microdata from the 2010 Brazilian census. Counter-intuitively we find that the gender earnings gap in favor of males widens with increased GDP per capita. Firstly, we find that females present higher schooling than males, which is consistent with the higher return to schooling among females. Secondly, the effect of the female schooling advantage on income is magnified by the local level of income inequality. Thirdly, through decomposition, we obtain the component due to discrimination (or any factor independent of schooling that undervalues female characteristics) against women. Finally, the explanation for the counter-intuitive result is that while gender discrimination reduces with GDP per capita, somehow the level of income inequality reduces more quickly, resulting in a gender earnings gap that widens with increased GDP per capita.

Keywords: Real options; Gender earnings gap; Development; Discrimination; Income inequality; Blinder–Oaxaca decomposition; Brazil
JEL classification: J16, J31, J71

I. INTRODUCTION

Economic development is associated with an increase in women's relative earnings. This convergence may be supported by several factors that accompany economic development, such as women's empowerment (Duflo 2012), the development of women's market skills (Blau and Kahn 1997), the decline of labor market discrimination (Blau 1998; Blau and Kahn 2000; Gunderson 1989), and the complementarity between capital and female labor (Galor and Weil 1996).

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

* Corresponding author: Silvio Hong Tiing Tai, Business School, PUCRS, Avenida Ipiranga, 6681, Porto Alegre, RS, 90619-900 Brazil. Email: silvio.tai@pucrs.br

 doi: 10.1111/deve.12187

Nevertheless, we find the opposite when analyzing the 2010 Brazilian census: the gender earnings gap in favor of men widens with increased GDP per capita. This paper provides an explanation for this unusual result based on the heterogeneity of income inequality and discrimination throughout Brazil.

Income inequality is affected by the wage structure, as it reflects the price of skills (Juhn, Murphy, and Pierce 1991). The rationale is that economies with high rates of return to schooling present high inequality in labor income, because the skill premium is large. Mincer (1970, p. 8) indicates that "Earnings inequality and skewness are also greater the higher the rate of return [to schooling]." Then, if males present a higher level of schooling than females, an increase in income inequality will represent an increase in the gender gap. Blau and Kahn (1992, 2003) find this result when comparing developed economies. However, in the current paper, females present higher levels of schooling than males, and therefore income inequality narrows the gender earnings gap. As income inequality diminishes with GDP per capita in Brazil, thus the narrowing effect of income inequality on the gender earnings gap diminishes with the increase in GDP per capita, what largely explains the positive correlation between the gender earnings gap and GDP per capita.

But, why is the level of female schooling higher than the level of male schooling? From the demand-side point of view, the straightforward answer is that persistent differences in return to schooling in favor of women are high enough,[1] causing an adaptation of female characteristics (Oaxaca 1973). Through Blinder–Oaxaca decomposition, we find that the difference in return to schooling is proportional to the magnitude of the effect of discrimination on the other variables[2] (which encompasses any factor that undervalues women's characteristics). This is in line with Dougherty (2005) who shows that discrimination is not uniform in the labor market and that it reduces as the level of education rises.[3] Education, in this case, may be thought of as a means by which women mitigate the effects of discrimination on earnings. We find that the effect of discrimination, even when discounting the effect of the difference in return to schooling, decreases with GDP per capita. This result is consistent with the expected convergence of gender equality and development. Alternatively, higher returns to schooling for females may also be explained by self-selection of females, as low-skilled women face higher rates of unemployment and are presumably more positively selected than men in the labor market.

[1] Deolalikar (1993) and O'Neill and Polachek (1993) also find higher returns to schooling for women than for men that are compatible to a relative increase in characteristics in favor of females.

[2] The component of discrimination is obtained by Blinder–Oaxaca decomposition as the gender difference of the coefficients of other variables than education.

[3] Other explanations include supply-side opportunities to study, as the release of girls from heavy work on rural localities.

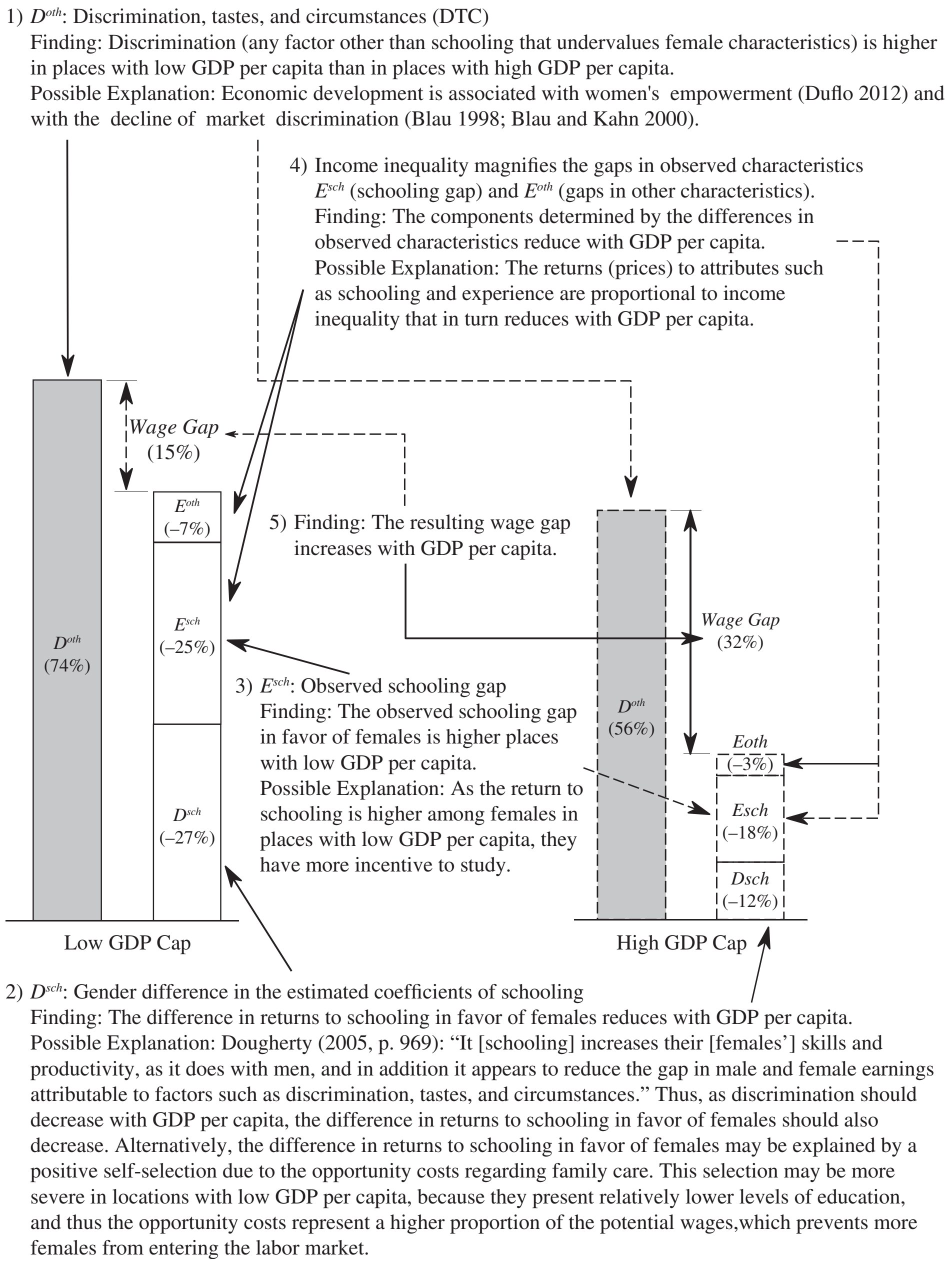
The contribution of this paper is threefold. Firstly, we show that market prices reduce the gender earnings gap, which is at odds with the literature (Blau and Kahn 1992, 2003), but consistent with the underlying economic mechanism. Secondly, we provide evidence that discrimination reduces with rising levels of education (Dougherty 2005), resulting in relatively greater levels of schooling and return to schooling among females. Thirdly, we show that, as the localities develop, both income inequality and discrimination decrease, although somehow the former shrinks at a much faster rate than the latter, which results in an increasing function of the gender earnings gap with increased GDP per capita. For the sake of clarity, in Figure 1, we present the main findings with correspondent possible explanations based on the literature.

A. *Brazilian Setting*

Brazil is an important place to study the gender gap, as the level of development and income inequality vary widely in the cross-sectional data. On the one hand, Brazil represents a large geographic heterogeneity in terms of development stages. The poorest locations are comparable to India while the richest are comparable to the peripheral countries in Europe. On the other hand, the country presents high levels of both intra- and inter-regional income inequality. In addition to its vast territory and colonization and settlement processes, Brazil presents other factors that contribute to the heterogeneities that characterize the country. Lovell (2000b) draws attention to the unequal processes of development with geographical and demographic polarization that have distinguished Brazilian society since the colonial period. Lovell (2000b) highlights the regional effects of the sugar, gold, and coffee booms, as the expansion of the sugar trade led to the importation of slaves to the northeast region. That area went into decline with the gold boom during which the productive importance shifted to the southeast region. In the aftermath, the concentration of wealth generated by the expansion of coffee farming allowed the beginning of industrialization in the country and its initial concentration in the southeast. Naritomi, Soares, and Assunção (2012) reinforce the importance of the historical process and point out that cities affected by the sugar and gold booms evolved with a high concentration of land ownership and less access to justice, respectively. Although some studies find signs of income convergence and inequality reduction in Brazil, the southeast region remains the economic and financial center of the country (Azzoni 2001). Table 1[4] and Appendix Figure 2 describe statistics of selected variables and illustrate the extent of regional disparities in Brazil.

[4] See the map of Brazilian states in Appendix Figure 1.

Fig. 1. Main Findings and Possible Explanations



The literature identifies some specificities of the gender gap in Brazil. Madalozzo (2010) suggests that job market regulation and maternity leave may be a

TABLE 1

Selected Variables at State Level

State	Ln(GDP per capita)	Return to Schooling (%)	Gender Earnings Gap (%)	Male Years of Schooling	Female Years of Schooling
Maranhão	1.60	11.6	7.8	5.88	6.74
Piauí	1.63	12.1	5.1	5.67	6.72
Alagoas	1.73	10.3	16.2	5.93	6.49
Paraíba	1.81	10.8	10.1	6.04	6.93
Ceará	1.89	7.6	0.0	6.38	7.13
Rio Grande do Norte	1.99	6.8	4.6	6.71	7.54
Pará	2.00	7.4	27.3	6.28	7.10
Pernambuco	2.05	6.9	20.7	6.58	7.22
Bahia	2.07	9.2	24.1	6.33	7.12
Acre	2.12	9.5	14.5	6.47	7.32
Sergipe	2.12	7.2	23.6	6.49	7.21
Amapá	2.19	5.0	5.1	7.82	8.63
Tocantins	2.19	7.2	15.1	6.88	8.06
Roraima	2.31	6.2	5.6	7.44	8.42
Rondônia	2.39	6.3	42.6	6.43	7.16
Goiás	2.46	1.7	33.5	7.28	8.01
Amazonas	2.51	5.8	20.7	7.30	7.84
Mato Grosso do Sul	2.55	3.3	32.4	7.47	8.04
Minas Gerais	2.56	3.6	31.3	7.09	7.67
Mato Grosso	2.65	2.8	33.9	7.04	7.88
Paraná	2.71	2.9	36.7	7.73	7.98
Espírito Santo	2.82	3.6	33.9	7.50	7.96
Rio Grande do Sul	2.83	3.1	32.5	7.78	8.23
Santa Catarina	2.87	2.2	37.6	7.93	8.09
Rio de Janeiro	2.91	−0.3	22.4	8.56	8.75
São Paulo	3.08	−0.4	28.4	8.44	8.62

competitive disadvantage for females. Lovell (2000a) highlights the recent history and the alternation between dictatorship and democracy, as the dictatorship hid inequality issues through Institutional Acts that banned, for instance, the discussion of racial and/or gender inequality in the country.

Our paper is related to Lovell (2000b), who compares job markets in Bahia and São Paulo in 1980 and 1991. Through Blinder–Oaxaca decomposition, she finds a higher gender earnings gap in favor of males in Bahia and higher discrimination against females in São Paulo. Although these results qualitatively contradict those of our paper, the economic contexts are quite different. The period studied by Lovell (2000b) precedes important improvements for women in Brazil. Female participation in the job market increased from 27% in 1980 to 53% in 2010 (Madalozzo and Mauriz 2012). Moreover, according to IPEA (2006), female schooling surpassed that of male schooling. In 1980, the average schooling of females was 3.7 years, while that of males was 4 years. In 2010, the female schooling increased to 7.5 years, overtaking the male average of 7.2 years.

Furthermore, Madalozzo and Martins (2007), Scorzafave and Pazello (2007), Madalozzo (2010), and Madalozzo and Mauriz (2012) investigate the evolution of the gender gap and identify its determinants, while Lovell (2000b) and Lima et al. (2015) analyze regional differences in the gender gap and associated factors.

The remainder of the paper is organized as follows. Section II outlines the theoretical framework. Section III presents the data applied and Section IV reports the main findings. Section V offers some final considerations.

II. THEORETICAL FRAMEWORK

We proceed to estimations in two steps. In the first step we use individual data from the 2010 Brazilian census and decompose the gender gap through the Blinder–Oaxaca procedure using two levels of geographical disaggregation: states (26) and micro regions (558). In the second step we compare the resulting components of those decompositions with GDP per capita and inequality levels of the states and micro regions, respectively.

In order to identify regional disparities in Brazil it is essential to geographically disaggregate the analysis. Most papers detail the analysis by political regions (Scorzafave and Pazello 2007; Madalozzo 2010; Madalozzo and Mauriz 2012) or states (Lovell 2000b). Such levels of disaggregation permit the identification of many aspects of inequality in Brazil, but they are insufficient to capture intrastate differences (e.g., capital versus countryside). Alternatively, the analysis could be disaggregated at the city level, although this may lead to idiosyncrasies. The rate of municipal emancipation in Brazil has been intense. Between 1984 and 2000, 1,405 new municipalities were created, 94.5% of which have fewer than 20,000 inhabitants (Magalhães 2007) and lack a consolidated job market. Consequently, in many small Brazilian municipalities the economy and job market are dependent on neighboring cities. To overcome this limitation, we disaggregate the analysis using the regional division proposed by the Brazilian Institute of Geography and Statistics (IBGE 1990), which established the so-called micro regions based on two basic indicators, namely, productive structure and spatial interaction.[5] Although the criteria defining micro regions are intended to ensure a certain homogeneity within micro regions, differences in labor

[5] The indicator "productive structure" is based in the primary productive structure (based on land use, agriculture orientation, dimensional structure of the establishments, production relationships, technological level, capital allocation, and degree of diversity in production) and industrial productive structure (based on the importance of each industrial agglomeration in the micro region, according to industrial processing and personnel employed). "Spatial interaction" is defined by the area of influence limited to the places involved in the harvest, processing, and shipping of rural products, and by the places involved in the distribution of goods and services to the countryside and other cities (IBGE 1990, p. 10).

markets regarding gender and income situations may remain. Thus, estimations of the gender gap and the components within a micro region are average measures. We suppose that heterogeneity within each micro region is not substantial; to illustrate, in 80% of Brazilian micro regions the relative standard deviation (standard deviation divided by the mean) of the log of the municipal GDP per capita is smaller than 5%, and in 98% of micro regions it is below 10%.

A. *First Step*

Following Blinder (1973) and Oaxaca (1973), the log income of individual i (Inc_i)of gender g is expressed by:

$$Inc_i = s_i\beta_s^g + \mathbf{X_i}\boldsymbol{\beta}_x^g + u_i, \tag{1}$$

where s_i is the individual's schooling,[6] $\mathbf{X_i}$ is a vector with individual and geographical characteristics, namely, *age, age*^{2}*, age*^{3}*, age*^{4}*, race*, *marital status*, *if lives with partner*, and *city*. Parameters β_s^g, $\boldsymbol{\beta}_x^g$ are the respective coefficient and vector of coefficients and u_i is the error term.

The estimated coefficients of equation (1) are applied in the calculation of the male–female difference of the log income, which can be expressed by:

$$Inc\ Gap = s^m\hat{\beta}_s^m - s^f\hat{\beta}_s^f + \mathbf{X^m}\hat{\boldsymbol{\beta}}_x^m - \mathbf{X^f}\hat{\boldsymbol{\beta}}_\mathbf{x}^\mathbf{f}, \tag{2}$$

where s^m is the average schooling of males, s^f is the average schooling of females, $\mathbf{X^m}$ is a vector with the average values of individual and geographical characteristics of males, and $\mathbf{X^f}$ is a vector with the average values of individual and geographical characteristics of females.

We decompose this gap following Neumark (1988),[7] who uses a pooled regression with males and females, as a benchmark. We regress the income equation three times. Firstly for males (g = m), secondly for females (g = f), and finally for the entire pooled sample (g = *). Then, we rearrange equation (2),[8] thus obtaining equation (3), where the gender differences of characteristics are weighted by the coefficients of the pooled regression (β_s^* and $\hat{\boldsymbol{\beta}}_x^*$) and the gender

[6] We follow Lemieux (2006) and also include the squared of schooling. We omit this term here for the sake of clarity.

[7] A concise explanation of Neumark (1988) decomposition is provided in http://siteresources.worldbank.org/INTPAH/Resources/Publications/459843-1195594469249/HealthEquityCh12.pdf.

[8] We add and subtract $\left(s^m - s^f\right)\hat{\beta}_s^* + \left(\mathbf{X^m} - \mathbf{X^f}\right)\hat{\boldsymbol{\beta}}_x^*$ in the right-hand side of equation (2).

differences of coefficients are weighted by the respective characteristic (s^m, s^f, $\mathbf{X^m}$, and $\mathbf{X^f}$).

$$Inc\ Gap = \underbrace{\left(\hat{\beta}_s^m - \hat{\beta}_s^*\right)s^m + \left(\hat{\beta}_s^* - \hat{\beta}_s^f\right)s^f}_{\substack{\Delta \text{ coefficients of schooling} \\ (D^{sch})}} + \underbrace{\left(s^m - s^f\right)\beta_s^*}_{\substack{\text{schooling gap} \\ (E^{sch})}}$$

$$+ \underbrace{\mathbf{X^m}\left(\hat{\boldsymbol{\beta}}_x^m - \hat{\boldsymbol{\beta}}_x^*\right) + \mathbf{X^f}\left(\hat{\boldsymbol{\beta}}_x^* - \hat{\boldsymbol{\beta}}_x^f\right)}_{\substack{\Delta \text{ other coefficients} \\ (D^{oth})}} + \underbrace{\left(\mathbf{X^m} - \mathbf{X^f}\right)\hat{\boldsymbol{\beta}}_x^*}_{\substack{\text{other charact. gap} \\ (E^{oth})}}. \tag{3}$$

Equation (3) can be simplified in equation (4), then the male–female earnings gap[9] is decomposed in four components, which are mainly attributed to the difference in the estimated coefficients of schooling D^{sch}, the observed schooling gap E^{sch}, the differences in the estimated coefficients of other individual and geographical characteristics[10] D^{oth}, and finally the gap in the other observed individual and geographical characteristics E^{oth}. We refer to D^{sch} as the "difference in return to schooling" and we refer to D^{oth} as "discrimination" (of factors other than schooling). We can interpret the latter component as the discrimination that women suffer relative to men, when neither are educated.

$$Inc\ Gap = D^{sch} + E^{sch} + D^{oth} + E^{oth}. \tag{4}$$

The terms associated with the differences of the coefficients gathered in D^{oth} are generally related to labor discrimination, but they capture any factor that undervalues female characteristics. This residual nature suggests that discrimination may be overestimated.[11] Dougherty (2005) includes tastes and circumstances as factors that can cause differences in the coefficients. According to him, women may have a taste for certain occupations that are underpaid and circumstances may impose a lower return to female characteristics as a trade-off with

[9] This gap and its four components are positive if male income is higher than female income and it is negative if female income is higher than male income.

[10] These characteristics include the continuous variables: *age*, *age*^{2}, *age*^{3}, *age*^{4}, and the dummy variables: *race*, *marital status*, *if lives with partner*, *city*.

[11] Even though Gunderson (1989) reports that even articles that exhaustively use control variables find a component attributable to discrimination, except if the article uses control variables that reflect discrimination itself.

time to care for children. In turn, "firms . . . disproportionately reward individuals who labored long hours and worked particular hours" (Goldin 2014, p. 1091). While tastes and circumstances may differ from discrimination in the labor market, they are not completely distinguished from discrimination in general. Societal expectations can lead men to job preferences that reflect a dominant role, and prompt women to assume a maternal vocation (Daymont and Andrisani 1984). We recognize the existence of unobserved factors in D^{oth}, we follow Dougherty (2005), and we relate D^{oth} to discrimination, tastes, and circumstances (henceforth, DTC).

This paper does not include in the first step controls for occupation. On the one hand, they may reflect societal expectations (Daymont and Andrisani 1984), while on the other hand, they may mediate the impact of schooling on earnings (Dougherty 2005). Angrist and Pischke (2009, p. 47) call occupations "bad control," as they may induce a bias in the schooling coefficient. As occupation is not controlled herein, the terms $D^{sch}$and D^{oth} capture unobserved characteristics associated with occupations. In the second step we test the sensitivity of unobservable characteristics in D^{sch} and D^{oth} to changes in market prices. Similarly, the possibility of selection bias is not controlled either. If discrimination against women varies across locations, this heterogeneity may influence the impact of unobserved factors on job market participation and wages differently throughout locations. In this case, the selection would also depend on the local discrimination of the unobserved factors related to females, which would be indistinguishable from the selection based on observed characteristics. Instead we focus on the analysis of the impact of DTC and income inequality on the earnings of individuals within the job market, following Blau and Kahn (1992).

B. *Second Step*

Once the four components of the gender earnings gap are estimated, we analyze the variations of the components with GDP per capita. We decompose the covariance between the logarithm of GDP per capita (*lgdpc*) with the gender earnings gap; as $Inc\ \ Gap = D^{sch} + E^{sch} + D^{oth} + E^{oth}$, then;

$$\begin{aligned}\mathrm{Cov}(lgdpc, inc\ gap) = {} & \mathrm{Cov}\left(lgdpc, D^{oth}\right) + \mathrm{Cov}\left(lgdpc, D^{sch}\right) \\ & + \mathrm{Cov}\left(lgdpc, E^{sch}\right) + \mathrm{Cov}\left(lgdpc, E^{oth}\right).\end{aligned}$$

We expect that discrimination DTC is negatively correlated with GDP per capita, as discrimination diminishes with economic development. However, what should we expect from the correlations of the three other components with GDP per capita? We assume that discrimination and inequality determine part of these components, as we detail below, resulting in a positive correlation between them and the logarithm of GDP per capita.

The term D^{sch} has a key role in the analysis, which is why we separate it from the others. Dougherty (2005, p. 969) considers schooling a means of reducing female discrimination, as he attributes this to a double effect of women's education: "It increases their skills and productivity, as it does with men, and in addition it appears to reduce the gap in male and female earnings attributable to factors such as discrimination, tastes, and circumstances." In this case, the difference in return to schooling D^{sch} may be seen as a "primary" offshoot of DTC D^{oth}, compensating the prejudice against women. In practice, this means that if this double effect is at play, then the return to schooling is greater for females than for males. This female advantage leads to a "secondary" offshoot of DTC: as incentives to study are greater for women, they anticipate this market bias (Oaxaca 1973) and their schooling is higher than male schooling,[12] which implies that the component E^{sch} contributes in favor of women and is positively correlated with D^{sch}. In turn, if D^{sch} may be seen as a "reaction" to discrimination, then D^{sch} and D^{oth} should both reduce with increased GDP per capita, and we expect that the portion of D^{sch} and E^{sch} determined by discrimination reduce with increased GDP per capita. Another possible explanation for the difference in return to schooling is a potential selection bias in the first step estimations, due to the fact that low-skilled women have high opportunity costs regarding family care. Thus, only those with the most valuable (unobserved) characteristics for the labor market can enter the job market and afford family care services. To illustrate, the average low-skilled female unemployment rate is 25% in the poorest regions (north and northeast) and 11% in the richest regions (south, southeast, and center-west). The corresponding figures for males are 15% and 5%, thus unemployment penalizes low-skilled women in the poorest regions more severely, resulting in higher positive selection of those females.[13]

The magnitude by which the gender schooling gap reduces the earnings gap depends on the local wage structure; higher prices imply greater reductions. According to equation (3), the income inequality level β^* may "magnify" the effect of a given schooling gap on E^{sch} and the gap in other attributes E^{oth}. As inequality is negatively correlated with GDP per capita, then we expect that the portions of E^{sch} and E^{oth} determined by inequality reduce with increased GDP

[12] In this case the gender schooling gap is negative, in favor of women. The terms *Inc Gap*, D^{sch}, E^{sch}, D^{oth}, E^{oth}, and schooling gap are positive when men out-earn women.

[13] The average rate of high-skilled female unemployment is 11% in the poorest regions (north and northeast) and 7% in the richest regions (south, southeast, and center-west). The corresponding figures for males are 6% and 3%.

per capita. For this analysis, the following regressions are estimated at state level and micro region level:

$$Component_i^k = \alpha_0^k + \alpha_1^k D_i^{oth} + \alpha_2^k Inequality_i^l,$$

where *Component* is D^{sch} if k = 1, E^{sch} if k = 2, and E^{oth} if k = 3, i stands either for states or micro regions, and *Inequality* is either the return to schooling if l = 1 or Gini index if l = 2.

Then, we predict the effect of discrimination and inequality on D^{sch}, E^{sch}, and E^{oth} by multipling the coefficients estimated by the determinant. For example, if we regress D^{sch} as a dependent variable, the estimated $\hat{\alpha}_1^k$ times the variable D^{oth} that provides the predicted effect of D^{oth} on D^{sch}. Then, we calculate the contribution of each predicted effect to the covariance with the log of GDP per capita.

III. DATA

The main data source is the 2010 Brazilian census, which provides individual data on earnings and hourly load. The data for GDP and population are from IPEAdata.[14] We restrict the sample to those individuals in the labor market aged from 24 to 64 years, which includes about 7.2 million people: 4.2 million males and 3 million females.[15]

The hourly income used in this study is calculated as the logarithm of the income from principal job divided by the hours worked by week in that job. The Brazilian census provides detailed data on income as income from principal job, income from other jobs, and income from sources other than jobs. However, these declared values are very sensitive information from the respondents' point of view, and measurement errors may compromise their quality. Table 1 details the distribution of some variables at the state level, ordered by the logarithm of GDP per capita. The income inequality level, estimated by the return to schooling,[16] is a decreasing function of GDP per capita, while the education level (both for males and females) is an increasing function of GDP per capita. It

14 Available at http://www.ipeadata.gov.br/.

15 This sample represents 69 million of people in the population: 39 million males and 30 million females.

16 The Gini index is also used as a measure of income inequality throughout the analysis, and the results are similar. The correlation between *Gini* and *Return to Schooling* is 0.8493. The latter is estimated following Lemieux (2006), with a quadratic specification considering the impact of schooling and squared schooling on the log income. We then calculated the marginal effect of schooling on the log income. See the distribution of female and male returns to schooling across states in Figure S1 in the Online Appendix of the "Supporting Information" section of this article.

is worth noting that these correlations correspond to the "modern" approach of Galor (2000, p. 706) (also Galor and Moav 2004), where in "sufficiently wealthy economies equality stimulates investment in human capital and economic growth."

The gender earnings gap in favor of men increases with GDP per capita and this trend is consistent with the gender difference in schooling, although females are more educated than males and this difference reduces with GDP per capita.

Another aspect of these descriptive statistics is the geographic distribution, with a division between the "poor" north and the "rich" south. Appendix Figure 2 details the distribution of these variables at micro region level, where this spatial contrast is more evident. Southern micro regions present higher GDP per capita, higher levels of schooling, higher gender earnings gap (despite large gaps in the north), and lower levels of inequality.

IV. RESULTS

Using individual data, we firstly decompose the gender earnings gap at state level and micro region level. Then, estimated components are used in the second step to analyze their variation with GDP per capita.

A. *First Step*

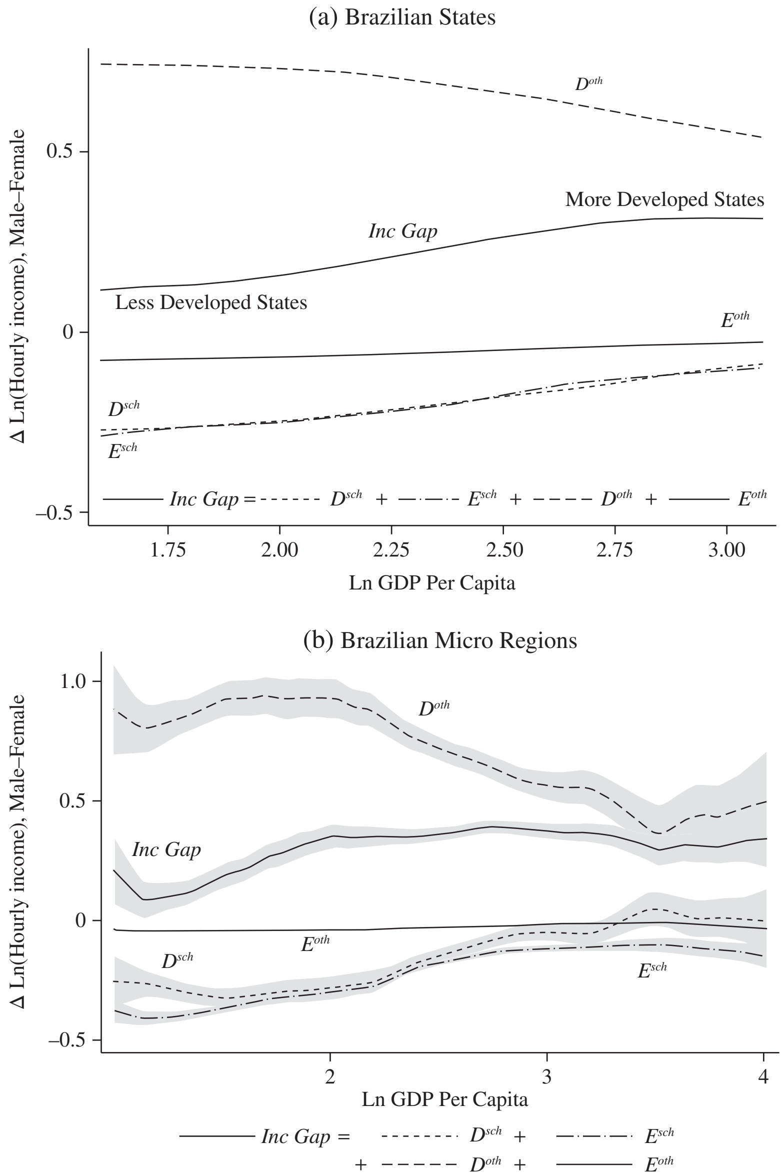
In the first step of estimations we proceed to decompositions at state level that provide 104 parameters, and at micro region level that provide 2,232 parameters.[17] For the sake of clarity, results are summarized through kernel-weighted local-mean smoothing[18] according to the logarithm of GDP per capita in Figures 2(a) and 2(b), respectively. Coefficients estimated at state level are reported in Appendix Table 1.

Although the poorer states of Brazil present smaller gender earnings gaps than the richer states, if we focus only on DTC (D^{oth}), it is a decreasing function of development. If we compare the local mean smoothing estimation of discrimination D^{oth} on the logarithm of GDP per capita (dashed line, in Figures 2(a) and 2(b)) with the local mean smoothing estimation of the resulting earnings gap on the logarithm of GDP per capita (continuous line), we

[17] Estimations at state level provide 104 parameters (26 states times 4 decompositions' components) and estimations at micro region level provide 2,232 parameters (558 micro regions times 4 decompositions' components).

[18] Local-mean smoothing is calculated with lpoly command in stata, which provides kernel-weighted local polynomial regressions. Local mean is obtained by setting the degree of the polynomial to zero.

Fig. 2. Gender Earnings Gap



Note: Graphic lines from local mean smoothing are predicted with the "*lpoly*" Stata command. GDP per capita values in 2010 parity purchase power (PPP) dollars. Countries described in X-axis of Figure 2(a) present comparable GDP per capita of the corresponding Brazilian states. Confidence intervals of 95% are depicted by the shadow around the lines in Figure 2(b).

notice that the gap in favor of men, due to discrimination, is reduced by the other components, and more so in the least developed states, reproducing a "rotation" of the dashed line to the continuous line.

B. *Second Step*

We calculate the average of each component and we decompose the covariance between the logarithm of GDP per capita (*lgdpc*) and the gender earnings gap (*inc gap*) as follows. The averages and the decomposition are reported in Table 2.

$$\begin{aligned}\mathrm{Cov}(lgdpc, inc\ gap) = {} & \mathrm{Cov}\left(lgdpc, D^{oth}\right) + \mathrm{Cov}\left(lgdpc, D^{sch}\right) \\ & + \mathrm{Cov}\left(lgdpc, E^{sch}\right) + \mathrm{Cov}\left(lgdpc, E^{oth}\right).\end{aligned}$$

The same pattern of averages and decomposition can be seen at both the state and micro regional levels. The average of the gender earnings gap is driven by the positive effect of DTC (D^{oth}), while the covariance of the gender earnings gap with the logarithm of GDP per capita is driven by the negative contributions of the other components. On the one hand, DTC (D^{oth}) presents a large and positive average that is higher than the sum of the averages of D^{sch}, E^{sch}, and E^{oth}. On the other hand, these remaining terms of the decomposition present positive covariances with the logarithm of GDP per capita, which, when summed together are greater than the covariance of DTC (D^{oth}) with the logarithm of GDP per capita, which "rotates" the dashed line in Figures 2(a) and 2(b) to the continuous line.

The analysis of the impact of DTC and income inequality on the earnings gap should be disaggregated at the component level, otherwise some mechanisms may not be identified in the aggregated variable of the earnings gap. To illustrate, the impact of DTC on earnings gap (D^{oth}) is negative but its offshoots are positive, and the overall impact of DTC on the earnings gap is the (residual) resultant of these opposite effects. Alternatively, the primary offshoot may be identified if one estimates the impact of DTC on D^{sch}, the secondary offshoot may be identified by the impact of DTC on E^{sch}, and the magnification may be identified by the impact of income inequality on E^{sch}.

We regress each component D^{sch}, E^{sch}, and E^{oth} on the determinants: DTC (D^{oth}) and income inequality. We use the estimated *Return to Schooling* to capture the level of income inequality within regions; we also use the Gini index to check for robustness. Once these determinants are estimated, we obtain the covariances between the logarithm of the level of GDP per capita and the portion of the components predicted by each determinant.

TABLE 2

Average of the Components and Covariance Decomposition of the Gender Earnings Gap

Component	State Level		Micro Region Level	
	Average	Cov. Dec. (%)	Average	Cov. Dec. (%)
Income gap	**0.22**	**100**	**0.30**	**100**
D^{oth}	0.67	−108	0.75	−172
D^{sch}	−0.19	102	−0.19	131
E^{sch}	−0.20	81	−0.23	128
E^{oth}	−0.06	25	−0.03	13

Table 3 shows the results of the regressions; columns (1) to (3) and (7) to (9) report estimations using return to schooling as a measure of income inequality and columns (4) to (6) and (10) to (12) report estimations using the Gini index. The component explained by the difference in return to schooling D^{sch} is regressed in columns (1), (4), (7), and (10). This component appears to present unobserved characteristics in favor of women that are magnified by income inequality, as the coefficient of *Return to Schooling* and *Gini* are negative and significant. However, and more importantly, it is highly determined by discrimination D^{oth}, with t-statistics about −11 for states and about −43 for micro regions. Considering the regression (1), if DTC (D^{oth}) is high enough, above 27%,[19] then schooling presents a compensating effect of DTC (D^{oth}), confirming the primary offshoot. In this case and taking the average of *Return to Schooling*, if a state increases its DTC levels from 27% to 28% (1 p.p.), *Return to Schooling* compensates it in 0.48 p.p., resulting in a net increase of 0.52 p.p. in the earnings gap. This suggests that the double effect (Dougherty 2005) is proportional to the DTC magnitude. By contrast, if the DTC level is below 27%, schooling does not reduce DTC, but contributes to it. This is not the case in our sample, as the lowest value of DTC (D^{oth}) is 29% for Rio de Janeiro (RJ). Alternatively, as both *Return to Schooling* and *Gini* are negatively correlated with GDP per capita, the negative coefficients of *Return to Schooling* and *Gini* may be explained by the fact that the self-selection of females is higher in locations with low GDP per capita than in locations with high GDP per capita.

Interestingly Figure 2(a) indicates that such a low level of DTC would occur in localities with higher GDP per capita than those in the sample, comparable to developed countries, where Blau and Kahn (1992) find higher skills prices for men than for women, and a consequent positive impact of income inequality on gender gap. Conversely, only the two most developed states in our sample present higher returns

[19] Taking the sample average of the *Return to Schooling* (0.12), $0.27 = -(-2.27 \times 0.12 + 0.40)/-0.48$.

TABLE 3

Determinants of the Gender Earnings Gap Components

	States			States			Micro Regions			Micro Regions		
	(1) D^{sch}	(2) E^{sch}	(3) E^{oth}	(4) D^{sch}	(5) E^{sch}	(6) E^{oth}	(7) D^{sch}	(8) E^{sch}	(9) E^{oth}	(10) D^{sch}	(11) E^{sch}	(12) E^{oth}
D^{oth}	−0.48***	−0.12***	−0.044**	−0.50***	−0.14**	−0.045**	−0.50***	−0.015	−0.014***	−0.53***	−0.076***	−0.017***
	(0.040)	(0.044)	(0.020)	(0.051)	(0.057)	(0.021)	(0.012)	(0.011)	(0.0029)	(0.012)	(0.012)	(0.0028)
Return to Schooling	−2.27***	−2.72***	−0.75***				−0.95***	−2.66***	−0.17***			
	(0.32)	(0.35)	(0.16)				(0.11)	(0.098)	(0.026)			
Gini				−1.14***	−1.39***	−0.44***				−0.35***	−1.28***	−0.092***
				(0.24)	(0.27)	(0.096)				(0.066)	(0.064)	(0.015)
Constant	0.40***	0.20***	0.061***	0.84***	0.74***	0.24***	0.30***	0.088***	−0.0030	0.41***	0.57***	0.033***
	(0.037)	(0.040)	(0.019)	(0.14)	(0.15)	(0.055)	(0.013)	(0.011)	(0.0030)	(0.037)	(0.036)	(0.0084)
Observations	26	26	26	26	26	26	558	558	558	558	558	558
R^2	0.932	0.821	0.640	0.890	0.697	0.633	0.812	0.626	0.166	0.798	0.495	0.162

Note: Standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

to schooling for males (see Online Appendix). The results obtained by Blau and Kahn (1992) obey the same economic mechanism observed here, but in the opposite direction: income inequality magnifies characteristics that benefit men.

In Table 3, columns (2), (5), (8), and (11) regress the schooling gap E^{sch} on DTC and income inequality. The predicted effect of DTC on E^{sch} is indirect: as DTC is lower for higher levels of education, the return to schooling of females is higher than that of males. It encourages women to study more, increasing their income, which we call the secondary offshoot of DTC. The impact of income inequality, in turn, magnifies the effect of the female schooling advantage. Both impacts are seen, as the coefficients of DTC and income inequality, respectively, are negative and significant, with the exception of regression (8) where the coefficient of DTC is not significant.

Columns (3), (6), (9), and (12) regress the component E^{oth} (the gap induced by the other characteristics) on their determinants, the coefficients of which are negative and significant, although they are smaller than those of columns (2), (5), (8), and (11). This suggests that discrimination may also have a primary offshoot in the other characteristics that are advantageous for women, and that income inequality magnifies the effect of those characteristics.

The results reported in Table 3 are used to calculate the covariances between the logarithm of GDP per capita and the portion of the components predicted by each determinant. For instance, the predicted portion of D^{sch} determined by *Return to Schooling* in column (1) is given by $-2.27 \times$ *Return to Schooling*. Table 4 reports the contribution to the covariance of each determinant on each component, at the state level. The predicted portion of D^{sch} determined by *Return to Schooling* contributes to 54% of the covariance between the logarithm of GDP per capita and the gender earnings gap. Although the theoretical model suggests only discrimination and income inequality as determinants, not all the above covariance is explained by the determinants, with a residual of 17% and 28% remaining at state level and 50% and 72% at micro region level.

Focusing on the state level in column (1), the component DTC (D^{oth}), as obtained previously, contributes to -108% of the covariance between the logarithm GDP per capita and the earnings gap. The primary offshoot of DTC is identified by the portion of D^{sch} determined by D^{oth} and it contributes to the covariance between the logarithm of GDP per capita and the earnings gap with 52%. The secondary offshoot of DTC is identified by the portion of E^{sch} determined by the DTC D^{oth}; and contributes to the covariance between the logarithm GDP per capita and the earnings gap with 13%. If we place the contribution of the portion of E^{oth} determined by the DTC D^{oth} (which is 5%) as the primary offshoot, the sum of the contributions of the offshoots with the contribution of discrimination D^{oth} is negative ($-108\% + 52\% + 13\% + 5\% = -38\%$), which is reassuring: the offshoots do not surpass their causation. The negative sign is inverted only

TABLE 4

Decomposition of Covariance between Ln(GDP per capita) and the Gender Earnings Gap

Component	Determinant	States (%)		Micro Regions (%)	
		(1)	(2)	(3)	(4)
D^{oth}	(1)	−108	−108	−172	−172
D^{sch}	(2) D^{oth}	52	54	86	91
	(3) *Return to Schooling*	54		33	
	(3) *Gini*		40		19
E^{sch}	(4) D^{oth}	13	15	3	13
	(5) *Return to Schooling*	57		92	
	(5) *Gini*		49		69
E^{oth}	(6) D^{oth}	5	5	2	3
	(7) *Return to Schooling*	16		6	
	(7) *Gini*		16		5
Residual		17	28	50	72
Discrimination + Offshoots (1) + (2) + (4) + (6)		−38	−34	−81	−65
Magnifications due to income inequality (3) + (5) + (7)		127	105	131	93

when the effect of income inequality is added (54% + 57% + 16%), which largely determines the covariance between the logarithm of GDP per capita and the earnings gap (127%). Column (2) shows similar results that are obtained when the Gini index replaces the variable *Return to Schooling*. Nevertheless, the residual is higher, due to the better fitness of *Return to Schooling* that is estimated using the same specification of the Blinder–Oaxaca decomposition.

The results for the micro regions present higher residuals than the results for the states, as they present lower fitness in Table 3. The micro regions present more idiosyncratic factors, which increases the variability in the estimations. For instance, some micro regions are predominantly rural, or present an overly representative proportion of civil servants. Despite this, however, the effects of discrimination and income inequality are confirmed. DTC and its offshoots would produce a negative covariance between the earnings gap and the logarithm of GDP per capita, explaining −81% and −65% of this covariance, according to columns (3) and (4),

TABLE 5

Determinants of the Gender Earnings Gap

	Gender Earnings Gap	
	(1)	(2)
Ln(GDP per capita)	0.105*	0.0686*
	(0.0489)	(0.0288)
D^{oth}	0.462***	0.397***
	(0.0626)	(0.0259)
Return to Schooling	−3.006*	−1.805**
	(1.409)	(0.440)
Constant	−0.0354	0.00827
	(0.322)	(0.0558)
Observations	26	558
R-squared	0.936	0.841
Dummy control	Region	Meso region

Note: Robust standard errors are in parentheses.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

respectively. Considering the residuals, if the effects of income inequality are not taken into account, the earnings gap would be reduced, or would vary little in relation to GDP per capita. In turn, income inequality essentially explains the positive correlation between the logarithm of GDP per capita and the gender earnings gap (131% and 93% in columns (3) and (4), respectively).

Finally, if, alternatively, we regress the aggregated earnings gap solely on DTC (D^{oth}) and on income inequality (*Return to Schooling*), we obtain: $Earnings\ Gap = 0.66 + 0.35\ D^{oth} - 5.74\ return$. In this case, the component DTC explains −38% of the covariance and the component income inequality explains 127% of the covariance, which corresponds to the last two rows of specification (1) in Table 4.

Both income inequality and discrimination impact the components of the gender earnings gap and are correlated with the log of GDP per capita. Thus, it may be natural to directly regress the gender earnings gap on income inequality, discrimination, and log of GDP per capita. We conduct this estimation at state level and micro region level and the results are reported in Table 5. At state level we include dummy variables to control characteristics and factors specific to regions, and at micro region level we include dummies specific to meso regions.[20] We confirm previous qualitative results that indicate a positive correlation of gender earnings gap with GDP per capita and DTC, and a negative correlation of gender earnings gap with return to schooling. Column (1) of Table 5 reports the results

[20] Meso regions are subdivisions of the Brazilian states, grouping together various micro regions. There are 136 meso regions in the 2010 data, resulting in an average of 4.1 micro regions per meso region.

at state level; the coefficients of the log of GDP per capita and return to schooling are statistically significant at 10%. One standard deviation of these variables impacts the gender earnings gap by 4.4[21] p.p. and −6.5 p.p. respectively. The coefficient of DTC is significant at 1% and one standard deviation of DTC widens the gender earnings gap by 7.9 p.p. At the micro region level, the log of GDP per capita, DTC, and return to schooling are significant at 10%, 1%, and 5%, respectively. One standard deviation of these variables impacts the gender earnings gap in 4.5 p.p., 13.6 p.p., and −6.9 p.p., respectively.

C. *Discussion of the Results*

The gender earnings gap presents a positive correlation with GDP per capita, although DTC, even when offshoots are discounted, presents a negative correlation. This puzzling result may be because the level of income inequality reduces with GDP per capita faster than the level of DTC. Hypothetically, if DTC reduced at a sufficiently fast rate, compared to income inequality, development would be associated with a *reduction* in the gender earnings gap, rather than an increase.

Figures 3(a) and 3(b)[22] confirm that inequality (captured by *Return to Schooling*) reduces with GDP per capita faster than DTC. These figures plot the variations of key variables in this study (DTC, return to schooling, and earnings gap) with the logarithm of GDP per capita through local mean smoothing regressions. The reduction of DTC with GDP per capita is steeper than the reduction of *Return to Schooling* with GDP per capita. As the earnings gap is positively correlated with DTC and negatively correlated with *Return to Schooling*, we can loosely think of the earnings gap as a possible function of the difference between them, as illustrated in the graphs by the dimension lines with arrowheads. Thus, the dimension lines increase with GDP per capita, as does the earnings gap.

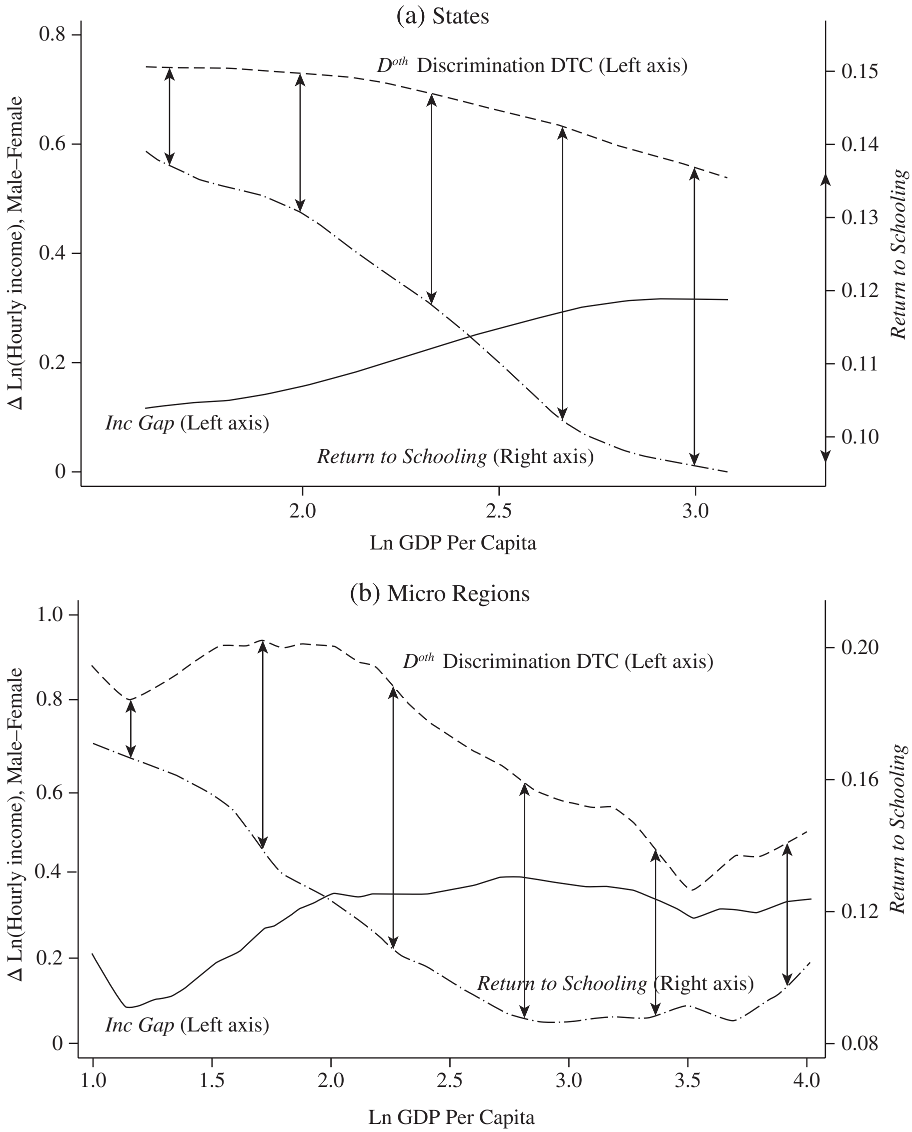
One can notice that the Brazilian micro regions climb the initial rungs of the development ladder, reducing income inequality much faster than they reduce DTC, in such a way that the gender earnings gap is widened. This is predominantly the case in the north and northeast regions. One possible explanation is that in the early stages of development, economic transformations, such as the reduction in income inequality, occur faster than cultural transformations, such as the reduction in DTC.

The most developed localities in Brazil, the south, southeast, and center-west, present a slightly different situation. The increase in GDP per capita is associated

[21] This number results from the multiplication of each variable's coefficient and standard deviation (e.g., for the log of GDP per capita the multiplication is given by $0.105 \times 0.4196863 = 0.044$).

[22] Appendix Figures 3(a) and 3(b) provide the same graphics using Gini as an income inequality measure.

Fig. 3. Variations of Gender Earnings Gap, Discrimination, and Return to Schooling with the Log of GDP Per Capita



with a reduction in DTC and a reduction in the income inequality level, which are more proportional to each other, resulting in relatively lower increments in the gender earnings gap. This fact suggests that, if the level of development is high enough, the pace of cultural transformations would be comparable to that of economic transformations.

V. CONCLUSION

This article investigates the gender earnings gap across Brazilian geographical regions, using individual data from the 2010 Brazilian census. Unexpectedly, the observed gender gap is an increasing function of the development level, at both levels of disaggregation. We proceed to a Blinder–Oaxaca decomposition and we aggregate the results in four components. The DTC component (discrimination, tastes, and circumstances) is defined based on the gender difference coefficient of the other characteristics, with the exemption of education. If the earnings gap were only determined by DTC, men would earn three times more than women, and the gap would be negatively correlated with GDP per capita.

Nevertheless, when compared with the baseline DTC, the other three components of the gender earnings gap mitigate the gap and revert its correlation with GDP per capita. Their impacts are in favor of women and they are positively correlated with GDP per capita. Firstly, the coefficient of education is greater for females than for males, indicating that education not only increases female productivity, but also reduces the effect of DTC. Moreover, this difference in education coefficients reduces the earnings gap proportionally to the magnitude of the effect of DTC. Secondly, as the return to schooling is higher for women than for men, women have more incentives to study and they present higher levels of education than men. In turn, since income inequality increases with GDP per capita, the female advantage in education is higher rewards in the least developed locations. Finally, females present other observed individual and geographical characteristics (besides schooling) that are better paid than those of men, and this reward is also magnified by the higher income levels in the least developed locations.

While the sign and magnitude of DTC predominates, with a positive earnings gap in favor of males, the correlation of income inequality with GDP per capita predominates, with a resulting gender earnings gap that widens with the increase in GDP per capita. At one extreme, in the least developed locations, discrimination against women is higher than in any other place; but it is more than offset by the relatively greater schooling of females associated with high levels of local income inequality, resulting in the narrowest gender earnings gap.

REFERENCES

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Azzoni, Carlos R. 2001. "Economic Growth and Regional Income Inequality in Brazil." *Annals of Regional Science* 35: 133–52.

Blau, Francine D. 1998. "Trends in the Well-Being of American Women, 1970–1995." *Journal of Economic Literature* 36, no. 1: 112–65.

Blau, Francine D., and Lawrence M. Kahn. 1992. "The Gender Earnings Gap: Learning from International Comparisons." *American Economic Review* 82, no. 2: 533–38.

———. 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics* 15, no. 1, pt. 1: 1–42.

———. 2000. "Gender Differences in Pay." *Journal of Economic Perspectives* 14, no. 4: 75–99.

———. 2003. "Understanding International Differences in the Gender Pay Gap." *Journal of Labor Economics* 21, no. 1: 106–44.

Blinder, Alan S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources* 8, no. 4: 436–55.

Daymont, Thomas N., and Paul J. Andrisani. 1984. "Job Preferences, College Major, and the Gender Gap in Earnings." *Journal of Human Resources* 19, no. 3: 408–28.

Deolalikar, Anil B. 1993. "Gender Differences in the Returns to Schooling and in School Enrollment Rates in Indonesia." *Journal of Human Resources* 28, no. 4: 899–932.

Dougherty, Christopher. 2005. "Why Are the Returns to Schooling Higher for Women than for Men?" *Journal of Human Resources* 40, no. 4: 969–88.

Duflo, Esther. 2012. "Women Empowerment and Economic Development." *Journal of Economic Literature* 50, no. 4: 1051–79.

Galor, Oded. 2000. "Income Distribution and the Process of Development." *European Economic Review* 44, nos. 4–6: 706–12.

Galor, Oded, and Omer Moav. 2004. "From Physical to Human Capital Accumulation: Inequality and the Process of Development." *Review of Economic Studies* 71, no. 4: 1001–26.

Galor, Oded, and David N. Weil. 1996. "The Gender Gap, Fertility, and Growth." *American Economic Review* 86, no. 3: 374–87.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104, no. 4: 1091–119.

Gunderson, Morley. 1989. "Male–Female Wage Differentials and Policy Responses." *Journal of Economic Literature* 27, no. 1: 46–72.

Instituto Brasileiro de Geografia e Estatística (IBGE). 1990. *Divisão regional do Brasil em mesorregiões e microrregiões geográficas*, vol. 1. Rio de Janeiro: IBGE. https://biblioteca.ibge.gov.br/visualizacao/monografias/GEBIS%20-%20RJ/DRB/Divisao%20regional_v01.pdf (accessed December 12, 2017).

Instituto de Pesquisa Econômica Aplicada (IPEA). 2006. *Ipeadata*. Rio de Janeiro: IPEA. http://www.ipeadata.gov.br/Default.aspx (accessed December 22, 2017).

Juhn, Chinhui; Kevin M. Murphy; and Brooks Pierce. 1991. "Accounting for the Slowdown in Black–White Wage Convergence." In *Workers and Their Wages: Changing Patterns in the United States*, edited by Marvin H. Kosters. Washington, DC: AEI Press.

Lemieux, Thomas. 2006. "The 'Mincer Equation' Thirty Years after Schooling, Experience, and Earnings." In *Jacob Mincer: A Pioneer of Modern Labor Economics*, edited by Shoshana Grossbard. New York: Springer.

Lima, Patrícia Verônica Pinheiro Sales; Marina Rocha de Sousa; Ahmad Saeed Khan; and Leonardo Andrade Rocha. 2015. "Distribuição espacial da desigualdade de gênero no Brasil." *Revista internacional interdisciplinar INTERthesis* 12, no. 1: 292–320.

Lovell, Peggy A. 2000a. "Gender, Race, and the Struggle for Social Justice in Brazil." *Latin American Perspectives* 27, no. 6: 85–102.

———. 2000b. "Race, Gender and Regional Labor Market Inequalities in Brazil." *Review of Social Economy* 58, no. 3: 277–93.

Madalozzo, Regina. 2010. "Occupational Segregation and the Gender Wage Gap in Brazil: An Empirical Analysis." *Economia aplicada* 14, no. 2: 147–68.

Madalozzo, Regina, and Sergio Ricardo Martins. 2007. "Gender Wage Gaps: Comparing the 80s, 90s and 00s in Brazil." *Revista de economia e administração* 6, no. 2: 141–56.

Madalozzo, Regina, and Mariana Mauriz. 2012. "Does Investing in Education Reduce the Gender Wage Gap? A Brazilian Population Study." *Population Review* 51, no. 2: 59–84.

Magalhães, João Carlos. 2007. "Emancipação político-administrativa de municípios no Brasil." In *Dinâmica dos municípios*, organized by Alexandre Xavier Ywata Carvalho, Carlos Wagner Albuquerque, José Aroudo Moa, and Marcelo Piancastelli. Brasilia: Instituto de Pesquisa Econômica Aplicada (IPEA). http://www.ipea.gov.br/portal/index.php?option=com_content&view=article&id=5580 (accessed December 9, 2017).

Mincer, Jacob. 1970. "The Distribution of Labor Incomes: A Survey with Special Reference to the Human Capital Approach." *Journal of Economic Literature* 8, no. 1: 1–26.

Naritomi, Joana; Rodrigo R. Soares; and Juliano J. Assunção. 2012. "Institutional Development and Colonial Heritage within Brazil." *Journal of Economic History* 72, no. 2: 393–422.

Neumark, David. 1988. "Employers' Discriminatory Behavior and the Estimation of Wage Discrimination." *Journal of Human Resources* 23, no. 3: 279–95.

Oaxaca, Ronald. 1973. "Male–Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14, no. 3: 693–709.

O'Neill, June, and Solomon Polachek. 1993. "Why the Gender Gap in Wages Narrowed in the 1980s." *Journal of Labor Economics* 11, no. 1: 205–28.

Scorzafave, Luiz Guilherme, and Elaine Toldo Pazello. 2007. "Using Normalized Equations to Solve the Indetermination Problem in the Oaxaca–Blinder Decomposition: An Application to the Gender Wage Gap in Brazil." *Revista brasileira de economia* 61, no. 4: 535–48.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's website.

APPENDIX TABLE 1

Results of Blinder–Oaxaca Decomposition at State Level (First step)

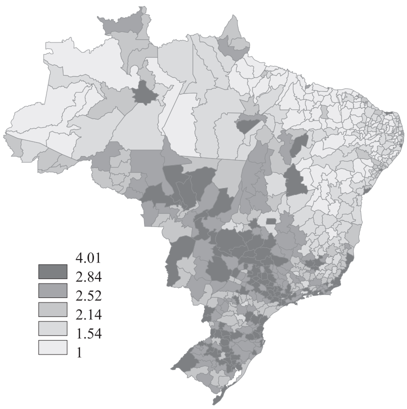
Region	State	Ln(GDP per capita)	*Inc Gap*	D^{oth}	D^{sch}	E^{oth}	E^{sch}	Obs.
Northeast	Maranhão	1.60	0.08	0.73	−0.25	−0.09	−0.31	202,260
Northeast	Piauí	1.63	0.05	0.77	−0.26	−0.11	−0.35	137,412
Northeast	Alagoas	1.73	0.16	0.84	−0.38	−0.05	−0.25	91,972
Northeast	Paraíba	1.81	0.10	0.83	−0.36	−0.07	−0.30	165,213
Northeast	Ceará	1.89	0.00	0.48	−0.13	−0.10	−0.25	244,209
Northeast	Rio Grande do Norte	1.99	0.05	0.56	−0.18	−0.08	−0.26	122,817
North	Pará	2.00	0.27	0.83	−0.27	−0.06	−0.22	205,469
Northeast	Pernambuco	2.05	0.21	0.76	−0.29	−0.04	−0.22	260,532
Northeast	Bahia	2.07	0.24	0.89	−0.35	−0.07	−0.23	480,475
North	Acre	2.12	0.14	0.78	−0.29	−0.08	−0.26	26,620
Northeast	Sergipe	2.12	0.24	0.84	−0.30	−0.07	−0.23	74,604
North	Amapá	2.19	0.05	0.48	−0.18	−0.04	−0.21	23,254
Center-west	Tocantins	2.19	0.15	0.83	−0.28	−0.08	−0.32	81,971
North	Roraima	2.31	0.06	0.60	−0.23	−0.06	−0.25	18,298
North	Rondônia	2.39	0.43	1.02	−0.33	−0.06	−0.20	69,424
Center-west	Goiás	2.46	0.34	0.57	−0.05	−0.04	−0.14	266,161
North	Amazonas	2.51	0.21	0.64	−0.22	−0.06	−0.16	79,761
Center-west	Mato Grosso do Sul	2.55	0.32	0.63	−0.11	−0.04	−0.16	101,803
Southeast	Minas Gerais	2.56	0.31	0.67	−0.16	−0.05	−0.15	901,437
Center-west	Mato Grosso	2.65	0.34	0.73	−0.16	−0.05	−0.18	140,273
South	Paraná	2.71	0.37	0.59	−0.09	−0.04	−0.10	504,164
Southeast	Espírito Santo	2.82	0.34	0.67	−0.15	−0.04	−0.14	153,382
South	Rio Grande do Sul	2.83	0.33	0.52	−0.04	−0.03	−0.12	578,363
South	Santa Catarina	2.87	0.38	0.53	−0.06	−0.02	−0.07	368,564
Southeast	Rio de Janeiro	2.91	0.22	0.29	0.02	−0.01	−0.09	423,252
Southeast	São Paulo	3.08	0.28	0.37	0.01	−0.01	−0.08	1,415,409

Appendix Fig 1. Map of Brazilian States

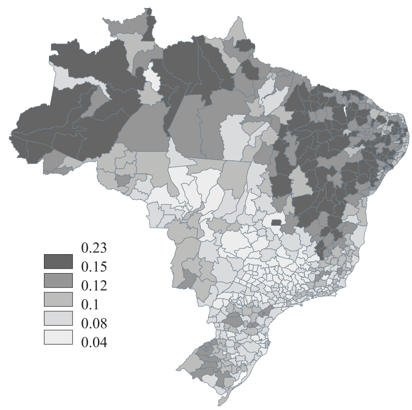
Source: The authors.

Appendix Fig 2. Selected Variables at Micro Region Level

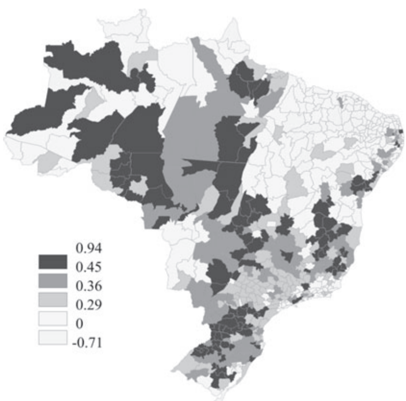
(a) Logarithm of GDP Per Capita



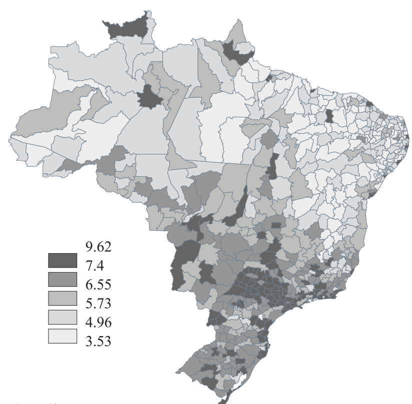
(b) Return to Schooling



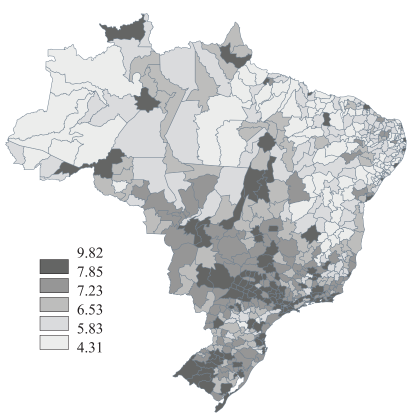
(c) Gender Earnings Gap



(d) Male Years of Schooling



(e) Female Years of Schooling



Appendix Fig 3. Variations of Gender Earnings Gap, Discrimination, and Gini with the Log of GDP Per Capita