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Article

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Gender wage discrimination in Brazil from 1996 to 2015: A matching analysis

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ABSTRACT

The discriminatory component of the gender wage gap was found to be significant and to decrease over time by previous studies, most of them based on the Oaxaca-Blinder decomposition (OBD). Such evidence is disputable for being grounded on the assumption of full common support between men and women, which has been increasingly refuted by international literature. Seeking to fill this gap for the case of Brazil, the paper revisits household survey data from 1996 to 2015 with propensity score (PS) and nearest-neighbour (NN) matching techniques. As results, the discriminatory component was confirmed to be significant in all years and not to follow a systematic decaying trend across the years – the fall observed from 1996 to 2004 was offset in 65% by a subsequent increase. Gender discrimination was heterogeneous throughout occupational categories, being especially high in management positions. Estimates, albeit belonging to the range of previous studies, also challenged the gap closing trend suggested by these studies. Given ongoing recession and high informality, it is uncertain whether further progress towards gender wage equality in Brazil will emerge spontaneously from the private sector or whether specific policy is needed.

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1. Introduction

There is wide and growing evidence of wage disadvantage for women. In fact, the gender wage gap was observed in all industries and occupations in most of the 177 countries covered in the latest edition of the United Nations' World's Women report (UN, 2015). The wage gap is greater at the end of the career (after 30 years of working in the same company) and in management positions (UN, 2015). The particular case of Brazil is no exception to the international pattern. Brazilian household survey data (PNAD) reveals the trend of the monthly individual wage in the main job of people aged 10 years or older (Fig. 1). It is noticeable that male wage was at least 1.5 times larger than female's from 2001 to 2015. The Global Economic Gap Index of 2016 from the World Economic Forum measures the inter-gender gap regarding the economic, cultural and political dimensions. The lowest value of the index, zero, indicates full inequality and the highest value, one, full equity. Brazil occupied the 79th position among the 144 countries considered (WEF, 2016). In terms of equitable pay

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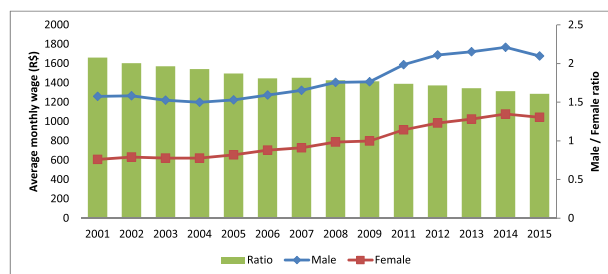


Fig. 1. Monthly average wage, male and female individuals aged 10 or older, Brazil, 2001–2015.

Source: IBGE, 2017, Brazilian Annual Household Survey (“PNAD anual”). The year 2010 was omitted due to absence of household survey (PNAD).

in similar occupations, the country ranked 129th and, in female political empowerment, 86th. The situation is similar in neighbouring countries, with no country from the Americas among the top 10 (WEF, 2016).

The evidence regarding the gender wage gap, although remarkable, is, rigorously, insufficient to conclude for existence (and persistence) of gender discrimination. This is due to two fundamental problems. Firstly, the “decomposition problem”, that is, the notion that only part of the wage difference is potentially due to discrimination, the remaining part resulting from disparity in attributes that influence working performance. This problem was already solved by Oaxaca (1973) and Blinder (1973), with an econometric decomposition technique that calculates the discriminatory component of the wage gap by comparing men and women with equivalent attributes (i.e., which are perfect substitutes in the labour market, Oaxaca, 1973). However, this is only possible if, strictly speaking, all relevant combinations of attributes observed for one sex are also observed for the other sex. Hence the second problem, of common support, which is ignored by the Oaxaca and Blinder technique (Frölich, 2007; Nopo, 2008, Rubin, 2001). Nevertheless, with the alternative technique of matching it is possible to identify the subset of the range of attributes for which there is common support (Nopo, 2008). For this reason, matching is here used to measure the discriminatory component of the wage gap with accuracy, as originally proposed by Frölich (2007) and Nopo (2008). Propensity score and nearest neighbour matching are employed to test two hypotheses regarding the Brazilian labour market from 1996 to 2015. The first is that the discriminatory component of the wage gap was favourable to males in all years of the period. The second hypothesis is that the parameter followed a downward trend across the period, as informed by previous studies (Madalozzo, 2010; Garcia et al., 2009; Giuberti and Menezes-Filho, 2005).

The text that follows departs from a literature review, in which both the method and the results of previous studies are examined. Methods and data are presented in the third section and results in the fourth section. A discussion confronts the results obtained with previous studies, followed by a brief section with final remarks.

2. Literature review

2.1. Wage gap and its determinants

According with Goldin (2014), the wage differential between genders should be already null currently, since women have a higher level of education and a comparable level of experience. However, the gap remains mainly in industries rewarding working through long hours and at specific times of the day, in which presence in the office is seen by employers as critical.

Kassouf (1998), based on data from the 1989’s wave of PNAD, estimated the counterfactual female salary that would prevail if female characteristics replaced male’s in the male remuneration equation. The great resulting difference between factual and counterfactual was taken as evidence of discrimination. Which was corroborated by the regionalized analysis of Cavalieri and Fernandes (1998).

In the same direction, Giuberti and Menezes-Filho (2005) measured gender wage discrimination in Brazil and the USA with data from the waves of 1981, 1988 and 1996 of the Current Population Survey (CPS) and PNAD. Results for Brazil pointed to an expected female wage larger than male’s in 18–22% in the period, due to women’s higher levels of education and experience. However, actual women’s wage was 17–40% lower. Such contradiction proves the considerable effect of gender discrimination, which was relevant both in the Brazilian and the American labour market. Notwithstanding, authors found wage differences to follow a decreasing trend over time in the two countries.

The Oaxaca-Blinder decomposition, estimated by Madalozzo (2010) with data for the years of 1978, 1988, 1998 and 2007 reiterates that, among individuals with similar attributes, a wage advantage prevails for men in Brazil. According to Madalozzo and Artes (2017), based on analysis of data from 2013, men have an average salary advantage in all comparative scenarios simulated, even though the share of women with more education has been higher in mixed and male-dominated professions. Women in traditional occupations (such as law, medicine and engineering), which are also male-dominated, or in the public sector, face a lower wage differential compared to other occupations. Similar evidence was obtained by Matos and Machado (2006) and Meireles (2014), with the first article arguing that the gender wage gap has changed little between 1987 and 2001.

2.2. Methodological issues and matching studies

The studies summarized so far have made an important contribution to the measurement of the gender wage gap in Brazil. Notwithstanding, the commonly used method of comparison, the OBD, confronts men and women who are not necessarily comparable. Comparability is only achievable by selecting men and women which are satisfactorily equivalent for two categories of variables. First, observable attributes that are relevant for the labour market, whose distribution generally differs between genders (Ñopo, 2008). Here, equalizing genders in terms of supports of distributions is required. Second, there are unobservable, but rather influential attributes, which may be correlated with observable attributes, such as the remuneration that was expected before entrance in the labour market (Azmat and Petrongolo, 2014).¹ These variables are not available in household surveys targeting labour and income, as is the case of PNAD.

The impossibility of identifying homogeneous groups in non-observables requires an identification strategy (Morgan and Winship, 2007; Angrist and Pischke, 2008). A solution is the combination of the hypotheses of ignorability of treatment assignment and of common support, which ground the matching method, an approach increasingly used in recent literature.

The pioneer study by Frölich (2007) formally demonstrated the possibility of using matching for applications other than the traditional treatment evaluation and, specifically, for the analysis of gender discrimination. As a proof of concept, the author applied propensity score matching to estimate the discriminatory component of the gender wage gap in the UK labour market. It turned out that a relevant part of the gap in wage was explained by the gap in the subject of degree in higher education. In fact, the inclusion of this explanatory factor increased the fraction of the explained gap from 46% to 66%, with the increase being even greater whether comparing high-income men and women.

Ñopo (2008), another pioneer study in the analysis of gender wage discrimination with matching, proposed a technique in which, building in the common range of supports, comparable synthetic gender pairs are created by sampling without replacement. The technique was applied to Peruvian data from 1986 to 2000. Fractions of 23% of men and 30% of women in the sample were not comparable (out-of-support). The discriminatory portion of the wage gap proved to be statistically significant. Ñopo's method (2008) has already generated multiple studies, especially in Latin America. An example is the study by Atal et al. (2009), applying the technique to 18 countries in Latin America in 2005, in which a statistically significant discriminatory component was also detected.

Meara et al. (2020) analysed data from the USA's CPS, 2011/2012 and 2017/2018 waves. Four estimators of matching were used, propensity score kernel, closest-neighbor, coarsened exact matching and regression adjustment with reciprocal weighting of probability (IPWRA). It was also employed the recentered influence function technique for OBD. Several control variables were accounted for, including immigrant and parenthood statuses, aiming to avoid omitted variable bias. In addition to univariate treatment, effects of bivariate treatments combining gender and unionization and gender and part-time work were also estimated. The discriminatory component of the gap was estimated at 15% based solely on gender and 31% based both on gender and part-time job, revealing the magnifying effect of a type of workday which is more frequent among women (in line with Goldin, 2014). Unionization, on the other hand, had a compensatory effect, albeit insufficient to fill the gap.

None of the matching studies mentioned refers specifically to the Brazilian case, thus perpetuating the lack of accurate evidence for the country. The present paper, therefore, provides a relevant contribution by analysing PNAD data with the matching technique.

3. Method and data

3.1. Method

3.1.1. Identification of the discriminatory component

The presentation here offered is an adaptation of Frölich (2007) and Noppo (2008). Both articles depart from OBD, which breaks down the wage gap into two components, one due to gender differences in relevant attributes to the labour market (education, experience, occupation, etc.), Δ_X , and the other due to differences regarding the marginal return of the attributes, Δ_β . The latter is generally associated with discrimination and the effects of unobservable factors. Denoting genders with "M" for male and "F" for female, the gap written as male surplus is:

$$\hat{\Delta} = (\overline{X_M} - \overline{X_F}) \hat{\beta}_F + (\hat{\beta}_M - \hat{\beta}_F) \overline{X_M} = \hat{\Delta}_X + \hat{\Delta}_\beta \quad (1)$$

Originally, the estimates for the parametric vectors, $\hat{\beta}_M$ e $\hat{\beta}_F$, are obtained from linear regressions (Oaxaca, 1973, Blinder, 1973, Jann, 2008). Such procedure ignores the impossibility of finding in the population, for some combinations of attribute levels, men (women), but not women (men). It is assumed, therefore, fully common supports even if this is not the case, incurring on inconsistent estimates of the gap components. This can be avoided by limiting the calculation of the differences

¹ Such variables are part of the random process through which genders self-select for economic activities and specific occupations (Meara et al., 2017).

to the common subrange of the supports, hereafter “S”, as the matching technique requires. The representation of the wage gap according to this method is shown below (Ñopo, 2008; Frölich, 2007).

$$\Delta = \int_S g_F(x) \cdot (f_M^S(x) - f_F^S(x)) dx + \int_S (g_M(x) - g_F(x)) f_M^S(x) dx = \Delta_X + \Delta_\beta$$

With $g_j(x)$ being the j th-gender specific function assigning wage to a value “ x ” of the attributes’ vector (“ X ”) and $f_j^S(\cdot)$ the vector’s distribution function for the j th gender which is defined on the common support (“ S ”). Thus, Δ_β corresponds to the average treatment effect on the treated (ATT), whether an analogy between the male gender and the treatment state is drawn.² That is, $\Delta_\beta = E[g_M - g_F|M]$, with the conditioning on M representing the male distribution of attributes. The identification of this parameter requires assumptions, given the counterfactual nature of $E[g_F|M]$, the wage that men would receive if they were assigned with marginal returns generally assigned to women. The first assumption adopted is the treatment assignment ignorability (Wooldridge, 2002), in the form $E[g_F|X, M] = E[g_F|X]$.³ Since the propensity score approach is chosen, the second assumption adopted is that of common support, i.e., $0 < P(M|X) < 1$ (Rosenbaum and Rubin, 1983a,b).⁴ It should be clarified that the propensity score, $P(M|X)$, can be understood as the probability that an individual has characteristics more frequently carried by male individuals. In short, the identification strategy presented consists of forming, from the propensity score, pairs of men and women satisfactorily homogeneous as to the vector of characteristics (X).

Taking into account the practice in the literature (Frölich, 2007, Meara et al., 2020, Dehejia and Wahba, 2002), three matching estimators are employed, comprising two estimators based on the propensity score (PS) that differ in probability density function (logistic or kernel; StataCorp, 2013, Leuven and Sianesi, 2003), and the non-parametric “nearest-neighbour” (NN) estimator. Estimators’ details are found in the appendix A. In order to obtain results robust to peculiarities of available computer routines, the estimators were, when possible, applied with two routines of the STATA® software, “psmatch2” (developed by users; Leuven and Sianesi, 2003) and “teffects” (developed by the manufacturer).⁵ In addition, only robust estimators for heteroscedasticity were used, according with the specification for the asymptotic variance proposed by Abadie and Imbens (2006).

The OBD technique was also applied in order to generate reference levels for measuring the size of the bias avoided by matching. The routine programmed by Jann (2008) was used, in which the ATT is obtained as Δ_β from the formula (1) above (details on OBD are found in Jann, 2008).

3.1.2. Matching diagnostic

As suggested in Imbens (2015), the homogeneity was performed to check for the level of balance before and after matching (i.e., to evaluate the degree of comparability within the pairs and, therefore, the matching quality). Following Rosenbaum and Rubin (1985) and Rubin (2001), the variance ratio was taken as the measure of homogeneity. It weights the coefficient vector by the variance-covariance matrix of the estimators. A variance ratio belonging to the intervals [0.5, 0.8) or (1.25, 2] is “of concern”, according to Rubin (2001). Balance is “bad”, i.e., there is no homogeneity, if the variance ratio is below 0.5 or above 2. Additionally, visual representations of matching quality were evaluated from the commonly used “balance” and “common support” graphs (see, for example, Dehejia and Wahba, 2002). The first compares the empirical distribution of propensity score for the sample as a whole (situation “before matching”) with that with the subsample containing males and only male-comparable females (“after matching”). It is expected, in the second situation, full or at least considerably greater homogeneity. The common support graph, for its turn, allows to check if there is, for both sexes separately, non-zero frequency of observations in each sub-interval of the propensity score range (i.e., the $[0; 1] \in \Re$ segment).

3.1.3. Heterogeneity of the discriminatory component

The discriminatory component estimated for the USA by Meara et al. (2020) differed with or without industry and occupation controls. Similarly, a considerable variation of the component was observed across occupational groups by Atal et al. (2009), (Fig. 2) with pooled data from eighteen Latin American countries. Under the light of these evidences, the possibility of ATT heterogeneity across the occupational dimension was verified by considering the nine largest occupations in relative frequency. These were grouped into four roughly equally likely classes in the sample, avoiding non-convergent or unreliable estimates due to scarcity of degrees of freedom. This exercise was carried out only for the most recent wave of PNAD of 2015.

² The metaphorical nature of the analogy with the treatment effect must be emphasized. Such analogy is used strictly to facilitate the exposure of the matching method. The latter, as Frölich (2007) demonstrates, has applications not restricted to the estimation of treatment effects, this being the crucial result basing our presentation.

³ This is, thus, one of the two conditions referred by Wooldridge (2002, cap.18, hypothesis ATE.1’) as ignorability of treatment in the form of conditional expectation.

⁴ The common support assumption ensures that all observations have positive probability of being treated and of being not treated.

⁵ The PS kernel estimator is only available in the psmatch2 routine and the PS logit, only in the teffects routine.

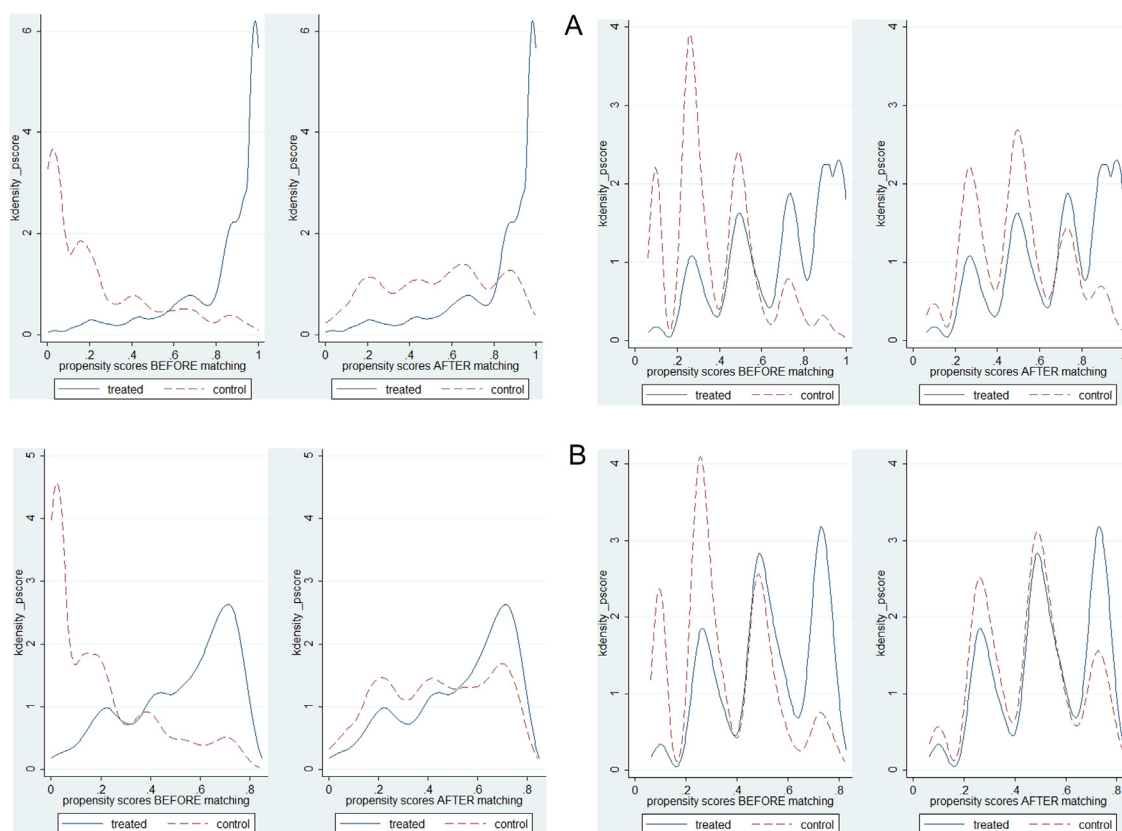


Fig. 2. Balance graphs, 1996 (left) and 2015 (right), subsample (panel A) and reduced subsample (panel B).

3.2. Data and variables

3.2.1. Data source

It is here analysed the microdata from the Annual Brazilian Household Survey (PNAD), waves of 1996, 2001, 2004, 2008, 2012 and 2015, as issued by the Brazilian Institute of Geography and Statistics (IBGE). The data was accessed via the “Data Zoom” STATA[®] routine.⁶ The hourly wage dependent variable was corrected for inflation based in the “IPCA” consumer price index, having 2015 as the reference year.

3.2.2. Variables

The explanatory variables were selected based on previous studies (Madalozzo, 2010; Madalozzo and Artes, 2017; Giuberti and Menezes-Filho, 2005; Garcia et al., 2009). Two measures of work experience were considered, (i) the traditional difference of current age and work starting age, and, for the years 2012–2015, (ii) the accumulated time in current employment (“tenure on the job”, Madalozzo, 2010). For the years 2012 and 2015, marital status was available and included as binary variables. Ethnicities were subdivided into three groups, (i) white and yellow (d.etnia_bca_ama), (ii) black and brown (d.etnia_pre_par) and (iii) indigenous and unstated, the latter being excluded from the data (Madalozzo, 2010). Additional variables included were occupation and industry dummies and whether the individual undertook household work (d.domest). Hourly wage outliers (bottom 5% and top 5%), individuals under 18 or over 64, pensioners, retirees, self-employed and non-salaried workers were excluded from the database.

The exclusions just mentioned resulted in a set of annual subsamples, hereafter referred as the “subsample”. The analysis of such data revealed further exclusions to be necessary due to the scarcity of women in the top 20% propensity score strata and consequent poorly balanced matching. The exclusion of the strata from the annual samples generated a dataset hereafter referred as the “reduced subsample” – the exclusion of observations with a propensity score unparalleled in the opposite group was recommended by Rubin (2001). The statistical summary of variables is found in Table 1 for the reduced subsample.

⁶ Details are found in the developers’ website: <http://www.econ.puc-rio.br/datazoom/microdados.html>.

Table 1
Description and summary of variables (reduced subsample).

Variable	Description	1996		2001		2004		2008		2012		2015	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
sal_hor	Hourly wage	7.475	6.095	6.924	5.315	6.767	5.050	7.904	5.390	9.214	6.229	9.914	6.557
d.hom	Male gender	0.306	0.461	0.307	0.461	0.347	0.476	0.364	0.481	0.380	0.485	0.379	0.485
d.etnia_bca_ama	White/yellow ethnicity	0.561	0.496	0.548	0.498	0.526	0.499	0.492	0.500	0.461	0.499	0.437	0.496
d.etnia_pre_par	Black/mixed ethnicity	0.439	0.496	0.452	0.498	0.474	0.499	0.508	0.500	0.539	0.499	0.563	0.496
anos_educ	Years of schooling	7.901	4.126	8.579	4.004	9.038	3.922	9.668	3.763	10.202	3.496	10.480	3.469
exper_idade_trab	Working experience	16.629	11.328	17.488	11.700	17.859	11.741	18.158	12.080	16.509	11.975	17.788	12.255
exper_idade_trab_sq	Work. Exper. (squared)	404.862	488.902	442.699	515.799	456.773	519.619	475.658	539.205	415.929	516.578	466.596	544.688
tenure_job	Tenure on the job	4.651	5.917	4.846	6.207	4.922	6.297	4.900	6.585	4.305	6.155	4.654	6.318
d.ativ_agro	I: Agriculture	0.024	0.152	0.017	0.130	0.020	0.140	0.017	0.129	0.009	0.097	0.007	0.084
d.ativ_indus	I: Manufacture	0.130	0.336	0.121	0.326	0.122	0.327	0.125	0.331	0.139	0.346	0.113	0.317
d.ativ_const	I: Construction	0.002	0.046	0.005	0.067	0.002	0.049	0.004	0.061	0.006	0.077	0.005	0.073
d.ativ_social	I: Education/Health/Social	0.259	0.438	0.248	0.432	0.200	0.400	0.199	0.399	0.171	0.377	0.192	0.394
d.ativ_serv	I: (other) Services	0.507	0.500	0.522	0.500	0.469	0.499	0.465	0.499	0.469	0.499	0.481	0.500
d.ativ_apub	I: Public administration	0.077	0.267	0.087	0.282	0.080	0.271	0.075	0.263	0.077	0.266	0.071	0.257
d.ocup_tec_cie_art	I: Science/Technology/Arts	0.175	0.380	0.171	0.376	NA	NA	NA	NA	NA	NA	NA	NA
d.ocup_adm	O: Management	0.213	0.410	0.201	0.401	0.191	0.393	0.203	0.402	0.227	0.419	0.219	0.414
d.ocup_agro	O: Agriculture	0.023	0.150	0.016	0.127	0.018	0.134	0.016	0.124	0.008	0.089	0.006	0.075
d.ocup_indus	O: Manufacture	0.070	0.255	0.067	0.249	NA	NA	NA	NA	NA	NA	NA	NA
d.ocup_com	O: Trade	0.130	0.336	0.136	0.343	0.097	0.296	0.096	0.295	0.120	0.325	0.114	0.318
d.ocup_transp_comu	O: Transport	0.013	0.111	0.012	0.108	NA	NA	NA	NA	NA	NA	NA	NA
d.ocup_serv	O: Service	0.265	0.441	0.270	0.444	0.377	0.485	0.357	0.479	0.317	0.465	0.331	0.470
d.ocup_dirigente	O: Top management	NA	NA	NA	NA	0.034	0.180	0.037	0.189	0.031	0.175	0.032	0.175
d.ocup_cie_art	O: Science/Arts	NA	NA	NA	NA	0.087	0.281	0.094	0.292	0.112	0.315	0.124	0.330
d.ocup_tec_med	O: Upper secondary technician	NA	NA	NA	NA	0.124	0.329	0.119	0.324	0.091	0.288	0.093	0.291
d.ocup_rep_manut	O: repair/maintenance	NA	NA	NA	NA	0.070	0.255	0.076	0.265	0.091	0.288	0.077	0.267
d.ocup_armada	O: Army	NA	NA	NA	NA	0.002	0.040	0.002	0.039	0.002	0.047	0.003	0.057
d.pocup_empo	PO: formal employee	0.452	0.498	0.443	0.497	0.476	0.499	0.520	0.500	0.596	0.491	0.602	0.489
d.pocup_mil	PO: Army	0	0	0.000	0.005	0	0	0.000	0.010	0.000	0.005	0.000	0.012
d.pocup_pub	PO: civil servant	0.157	0.364	0.145	0.352	0.130	0.337	0.126	0.332	0.107	0.309	0.106	0.308
d.pocup_out_scart	PO: informal employee	0.190	0.392	0.210	0.407	0.215	0.411	0.201	0.401	0.170	0.375	0.160	0.366
d.pocup_dom_cart	PO: Formal household worker	0.058	0.234	0.067	0.249	0.057	0.232	0.051	0.221	0.047	0.212	0.050	0.218
d.pocup_dom_scart	PO: Informal household worker	0.143	0.350	0.135	0.342	0.122	0.327	0.102	0.303	0.080	0.271	0.082	0.274
d.ref_fam	Household head	0.253	0.435	0.287	0.452	0.322	0.467	0.324	0.468	0.382	0.486	0.405	0.491
d.domest	Undertakes household work?	0.864	0.342	0.849	0.358	0.852	0.355	0.809	0.393	0.810	0.392	0.828	0.377
d.conju_s	Lives with spouse or partner?	NA	NA	NA	NA	NA	NA	NA	NA	0.341	0.474	0.344	0.475
d.conju_antes	Used to live with spouse or partner?	NA	NA	NA	NA	NA	NA	NA	NA	0.265	0.442	0.284	0.451
d.esta_civ_cas	Married?	NA	NA	NA	NA	NA	NA	NA	NA	0.070	0.255	0.064	0.244
d.esta_civ_dd	Divorced?	NA	NA	NA	NA	NA	NA	NA	NA	0.113	0.317	0.121	0.326
d.esta_civ_viu	Widow/er?	NA	NA	NA	NA	NA	NA	NA	NA	0.017	0.130	0.018	0.132
d.reg_1	Northern region	0.070	0.255	0.101	0.301	0.112	0.315	0.111	0.314	0.132	0.338	0.137	0.344
d.reg_2	Northeastern region	0.240	0.427	0.246	0.431	0.239	0.427	0.251	0.434	0.231	0.422	0.243	0.429
d.reg_3	Southeastern region	0.383	0.486	0.343	0.475	0.340	0.474	0.339	0.474	0.322	0.467	0.322	0.467
d.reg_4	Southern region	0.192	0.394	0.185	0.389	0.187	0.390	0.178	0.383	0.192	0.394	0.182	0.386
d.reg_5	Central-Western region	0.115	0.319	0.125	0.331	0.122	0.327	0.120	0.325	0.123	0.328	0.116	0.320
d.urbano	Urban area	0.923	0.266	0.945	0.229	0.937	0.243	0.936	0.244	0.954	0.209	0.952	0.214

Note: I = industry, O = occupation, PO = position in the occupation, M = mean, SD = standard deviation, NA = data variable not available for the period.

Table 2
Characteristics of observations excluded from the reduced subsample, all years as a whole.

Variable	Description	M	SD	M	SD	MR (E/I)	p-value
sal_hor	Hourly wage	7.05	4.97	7.97	5.84	89%	0
d_hom	Male gender	0.94	0.24	0.35	0.48	270%	0
d_etnia_bca_ama	White/yellow ethnicity	0.42	0.49	0.50	0.50	82%	0
d_etnia_pre_par	Black/mixed ethnicity	0.58	0.49	0.50	0.50	118%	0
anos_educ	Years of schooling	6.49	3.92	9.35	3.89	69%	0
exper_idade_trab	Working experience	20.48	12.07	17.50	11.89	117%	0
tenure_job	Tenure on the job	5.08	6.81	4.74	6.29	107%	0
d_ativ_agro	I: Agriculture	0.16	0.37	0.02	0.12	1041%	0
d_ativ_indus	I: Manufacture	0.24	0.43	0.12	0.33	195%	0
d_ativ_const	I: Construction	0.17	0.38	0.00	0.06	4351%	0
d_ativ_social	I: Education/Health/Social	0.01	0.10	0.21	0.41	5%	0
d_ativ_serv	I: (other) Services	0.29	0.46	0.48	0.50	61%	0
d_ativ_apub	I: Public administration	0.08	0.27	0.08	0.27	101%	0.3428

Note: MR mean ratio with excluded in the numerator. P-values for mean and proportion difference tests in the last row.

Table 3
Covariate imbalance, before and after matching, subsample and reduced subsample.^a

Estimator	Year	Subsample ($0 \leq \text{pscore} \leq 1$)				Reduced subsample $\text{pscore} \leq 0.8$			
		Before matching		After matching		Before matching		After matching	
		% W	% B	% W	% B	% W	% B	% W	% B
PS kernel	1996	27	36	21	0	30	18	0	0
	2001	21	36	24	0	31	22	9	0
	2004	23	31	29	3	29	20	3	0
	2008	23	31	14	0	26	23	3	0
	2012	20	33	5	3	28	18	5	0
	2015	15	35	8	0	23	25	3	0
NN mahalanobis (psmatch2)	1996	27	36	3	0	30	18	0	0
	2001	21	36	3	0	31	22	0	0
	2004	23	31	3	0	29	20	0	0
	2008	23	31	0	0	26	23	0	0
	2012	20	33	5	0	28	18	0	0
	2015	15	35	5	0	23	25	3	0

Note: %W = “worrying”, %R = “bad”.

^a The covariate imbalance test (pstest) is only available for the psmatch2 routine.

An examination of the excluded strata reveals it to be composed by males in 94%, with education one third lower, ten times more likely to work in agriculture, twice as likely to work in industry, forty times more likely to work in construction and twenty times less likely to work in education/health/social services (Table 2). Which further attests the dominantly male characteristics of the observations outside the common support domain of the covariates' space (in line with a propensity score above 80%).

4. Results

4.1. Diagnostic

According with Rubin's covariate imbalance diagnostic table (2001; Table 3 below), which is based in variance ratios, matching zeroed the number of variables classified as “bad” in almost every year – the baseline is the “before matching” situation, in which all men and women are confronted. The effect was greater for the reduced subsample, in which the number of “worrying” variables was reduced by up to 78% and the count of “bad” variables was reduced to zero for all years.

Inspection of the balance graphs (Fig. 2) shows that, for all estimators and years, the density curve for matched women (“control”) followed a similar trend to that of men (“treated”), thus mitigating the dissimilarity observed when all women were accounted for (as visible in the contrast of “before matching” and “after matching” graphs of each pair). However, in the subsample, there was no common trend for a propensity score greater than 80% (upper quintile). There were, therefore, levels of covariates for which comparable women were simply unavailable. In the reduced subsample, on the other hand, a common trend was dominant and, thus, comparability was greater. In fact, comparability achieved a level compatible with the article by Meara et al. (2020; see the balance graphs presented by the authors in the appendices).

Regarding common support (Fig. 3), the two groups had non-negligible frequencies for all intervals of the propensity score, with the exception of intervals close to one for the control group and close to zero for the treatment group. Common support was thus partial and comparability of groups was consequently limited. This inconvenience was attenuated in the reduced subsample.

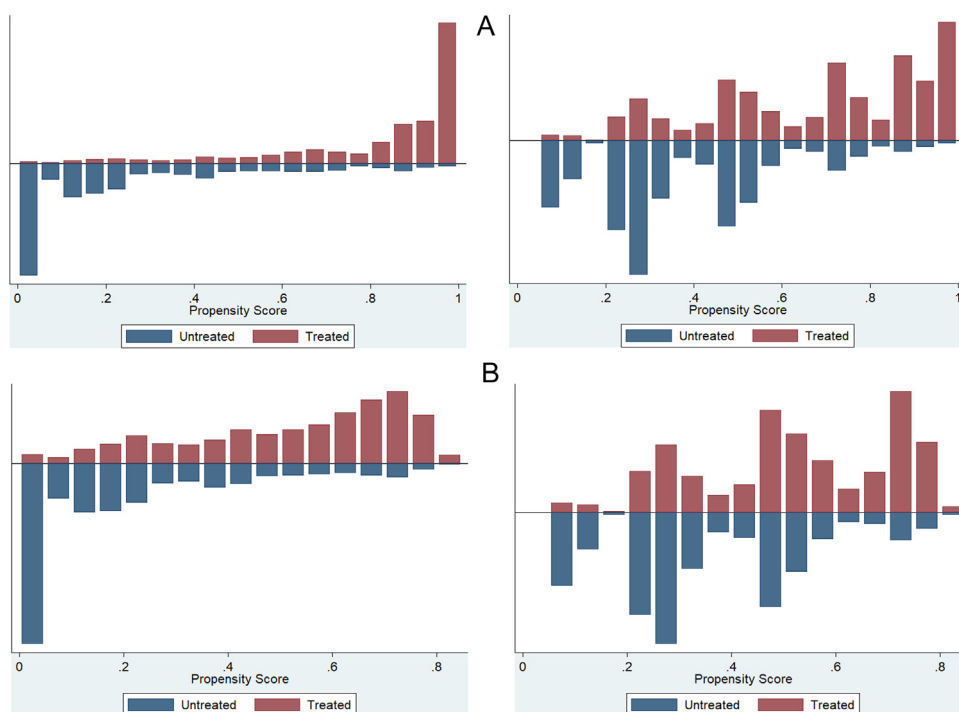


Fig. 3. Common support graphs, 1996 (left) and 2015 (right), subsample (panel A) and reduced subsample (panel B).

Table 4

Estimation results, 1996 to 2015.

MODEL	Year	ATT	ROB.SE	P-VALUE	C.I. 95%	N	Pairs
PS kernel	1996	1.47	0.12	0.00	1.23	1.70	37.129
	2001	1.18	0.09	0.00	1.00	1.36	47.130
	2004	0.97	0.07	0.00	0.83	1.12	58.698
	2008	1.11	0.07	0.00	1.26	0.97	65.899
	2012	1.06	0.10	0.00	0.87	1.25	45.365
	2015	1.26	0.10	0.00	1.05	1.46	43.823
NN mahalanobis (psmatch2)	1996	1.33	0.10	0.00	1.13	1.53	37.129
	2001	1.08	0.07	0.00	0.94	1.22	47.130
	2004	0.86	0.06	0.00	0.75	0.98	58.698
	2008	1.07	0.05	0.00	1.17	0.96	65.899
	2012	1.26	0.07	0.00	1.11	1.40	45.365
	2015	1.23	0.07	0.00	1.09	1.38	43.823
NN mahalanobis (teffects)	1996	1.34	0.10	0.00	1.15	1.53	37.129
	2001	1.07	0.07	0.00	0.93	1.22	47.130
	2004	0.87	0.06	0.00	0.75	0.99	58.698
	2008	1.07	0.05	0.00	0.96	1.18	65.899
	2012	1.25	0.07	0.00	1.10	1.39	45.366
	2015	1.24	0.08	0.00	1.10	1.39	43.823
PS logit	1996	1.42	0.11	0.00	1.21	1.64	67.174
	2001	1.06	0.09	0.00	0.88	1.24	47.159
	2004	0.91	0.07	0.00	0.78	1.04	58.698
	2008	1.07	0.06	0.00	0.94	1.19	65.899
	2012	0.99	0.08	0.00	0.83	1.16	45.366
	2015	1.16	0.09	0.00	1.36	1.67	43.823

Notes: ROB.SE = Robust standard error, C.I.= confidence interval.

4.2. Estimates for the discriminatory component

Only estimates obtained from the reduced subsample will be reported (Table 4), given the higher quality of matching and also the smaller discrepancy between estimators in terms of the time trend followed by the point estimates (Fig. 4).

The hypothesis of a significant and pro-male discriminatory component was not rejected for all years and all estimators, evidencing, thus, the existence of female wage discrimination (Table 4). The significant discrimination estimated adheres

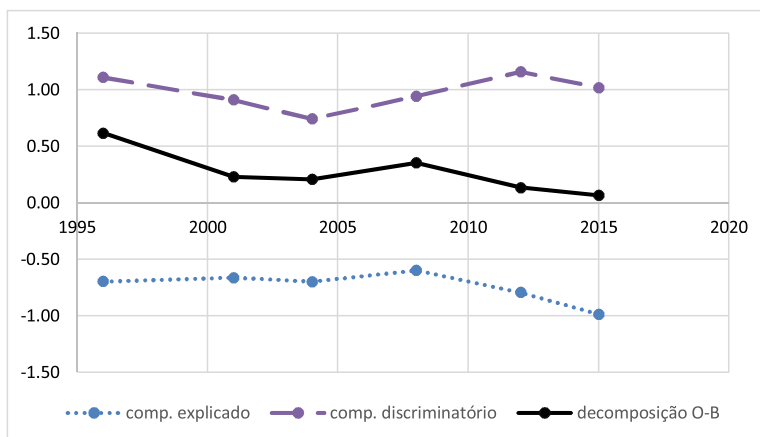
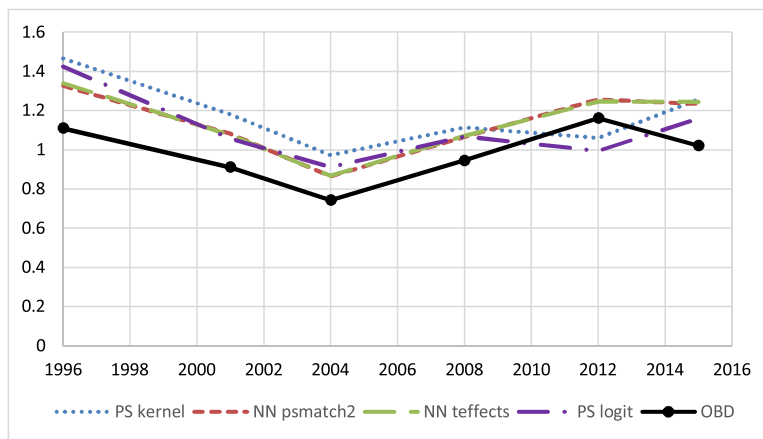
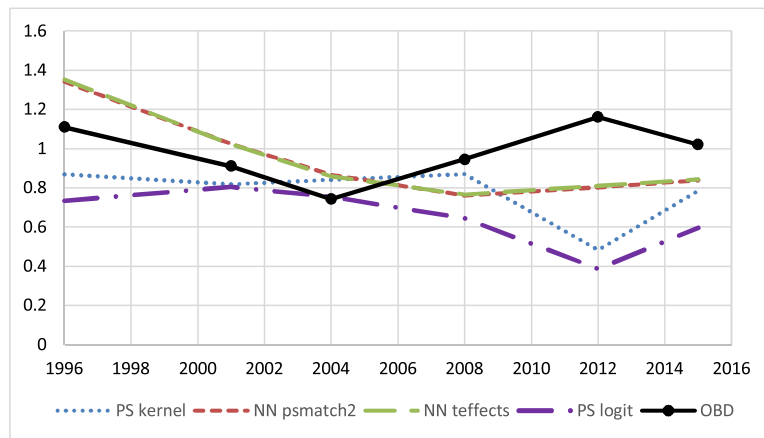


Fig. 4. Time trend of the discriminatory component, subsample (left) and reduced subsample (right).

to raw data patterns of the reduced subsample. Women’s education and experience were, respectively, 97% and 117% of men’s in the average year, and hourly wage was 86%. It is remarkable that women were also sixteen times more likely to be employed as informal household workers, from 2004 to 2015 (the subperiod for which the information was available), thus without labour rights, and also 2.4 fold more likely to undertake unpaid household work in the whole period. Regarding marital status, 84% of women never married.

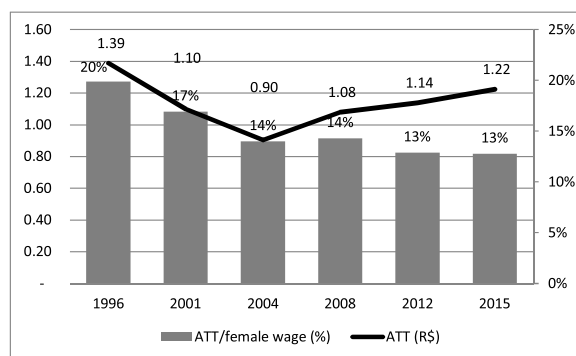


Fig. 5. Average estimate (ATT) (R\$) and percent estimate (ATT/average female wage)*.

*OBD is ignored and only the reduced subsample is considered. The range in USD is US\$0.23 (2004) to US\$0.36 (1996).

The second hypothesis, of a time-decaying discriminatory component, was refuted, since the downward trend was not absolutely dominant in the period.⁷ In fact, the trend was decreasing from 1996 to 2004 and non-decreasing thereafter, with the estimators then subdividing into two groups (Fig. 4). The first, composed by the nearest-neighbours and OBD estimators, followed an upward trend until 2012 and declined between 2012 and 2014. The second group, composed by propensity score estimators, followed an upward trend until 2008, declining from 2008 to 2012 and increasing from 2012 to 2014. The average estimator (Fig. 5, line plot) produced a falling discriminatory component until 2004, which increased thereafter to offset in 65% the initial drop. In summary, taking only the initial and final years of the period, a fall was observed. But this movement, as a more detailed examination reveals, was owned mainly to the turn of the century (from 1996 to 2004), and it was partially reverted by the upward trend observed in the XXIst century. Such pattern of variation resulted into a percent gap that, albeit falling across the period, remained nearly stable from 2004 to 2015 (Fig. 5, bar plot).

The discriminatory wage gap varied in the period between R\$ 0.90/hour and R\$ 1.39/hour (US\$0.23/hour to 0.36/hour),⁸ respectively 14% and 20% of the average female salary (Fig. 5), representing a female loss of, on average, R\$158.4–R\$222.4/month, for a 40 hours working week (US\$41 to US\$57).

Women thus faced an hourly wage loss that, even falling from 20% in 1996 to 13% in 2015, remained considerable at the end of the period. To better understand how considerable the loss actually was, a “gender tax” reasoning is convenient. Let it be considered the two main taxes on income in Brazil in 2015. First, the income tax upon annual wage,⁹ whose rate in 2015 was of 9% for private sector workers except those from the financial sector, and 11% for financial sector workers (CETAD-RF, 2017, tabela 13). Second, the “inflation tax”, whose rate was of about 11% per annum (IPEADATA, 2020b). The “gender tax rate”, calculated as $\frac{\text{before tax income} - \text{after tax income}}{\text{before tax income}} = \frac{\text{ATT}}{\text{average male wage}}$, was of 12%, nearly matching, therefore, the two main taxes on income in the country.

It is useful to report the main patterns from OBD estimation. The bias contained in the OBD estimator, contrary to the expectation (Ñopo, 2008), pointed downward (Fig. 4, at right). The estimates approached those of the nearest-neighbor estimator, both in level and trend. In addition, as Fig. 4 makes clear (right graph) even if OBD was not accurate for the treatment effect, it followed the same time trend of the accurate matching estimators. In fact, as each year was a different sample, OBD was satisfactorily able to capture the change in the samples’ central tendency albeit returning a biased estimate of the tendency’s level.

The heterogeneity analysis (Table 5) revealed that wage discrimination unfavourable to women was robust for the segmentation of the sample into occupational categories. This was true for management, production and service occupations, but not for the remaining occupations (“other” group, for which nonsignificance prevailed). Management occupations had a greater discriminatory component, a value of R\$1.27 or R\$ 1.4, depending on the estimator (US\$0.33 or US\$0.36).

5. Discussion

5.1. Adherence of results to the literature

A significant discriminatory component is a common result (Giuberti and Menezes-Filho, 2005; Madalozzo, 2010; Atal et al., 2009) and the estimates achieved fit the range of previous studies (Table 6).

Gender discrimination is also relevant under the light of economic experiments, as argued in the review by Azmat and Petrongolo (2014). Such studies found evidence of pro-male discrimination in the hiring processes of some activities in developed countries (e.g., in restaurants and orchestras in the USA). Multiple previous studies point to a drop in the

⁷ It should be reminded that the hourly wage was corrected for inflation, thus the time trends do not reflect monetary changes.

⁸ The exchange rate at the end of 2015, of R\$3.9402/US\$, is assumed throughout the paper (IPEADATA, 2020a).

⁹ This is the “imposto sobre rendimento do trabalho retido na fonte”.

Table 5
Heterogeneity analysis (subsample^c, 2015).

MODEL	Occupation ^{a,b}	ATT	ROB.SE	Z	C.I.	95%	N	Significance (p-value)
PS kernel	Management	1.27	0.22	5.90	0.85	1.70	11399	<1%
	Production	1.05	0.41	2.57	0.25	1.86	13851	5%
	Service	0.80	0.11	6.98	0.57	1.02	21529	<1%
	Other	-0.20	0.51	-0.40	-1.21	0.80	14516	No
NN mahalalanobis (psmatch2)	Management	1.40	0.15	9.03	1.09	1.70	11400	<1%
	Production	1.30	0.24	5.53	0.84	1.76	13851	<1%
	Service	0.99	0.08	12.56	0.83	1.14	21529	<1%
	Other	-0.14	0.19	-0.77	-0.51	0.22	14519	No

^a Management top management and remaining management positions, prod production (manufacture), repair and maintenance, serv services including trade, other science, arts, upper secondary technicians, agriculture, army.

^b The sample shares were of 18% for top manag., 23% for production, 34% for service and 25% for other.

^c Reduced subsample was avoided due to micronumerosity of the occupation categories.

Table 6
Discriminatory component of the gender wage percentage gap, compared to previous studies.

Source	Country	Period	Lower bound	Upper bound	Method
This paper	Brazil	1996 to 2015	13%	20%	Propensity score matching
Giuberti and Menezes-Filho (2005)	Brazil	1981, 1988 and 1996	20%	32%	OBD
Garcia et al. (2009)	Brazil	1996 and 2006	50%	60%	Matching <i>a la</i> Ñopo (2008)
Madalozzo and Artes (2017)	Brazil	2013	21%	23%	Mincerian regression with gender dummy
Madalozzo (2010)	Brazil	1978 and 2007 with ten year gaps	15%	33%	OBD
Meara et al. (2020)	USA	2011/ 2012 e 2017/2018	3%	18%	Propensity score matching
Atal et al. (2009)	Brazil	2005	26%	31%	Matching <i>a la</i> Ñopo (2008)
Literature range			3%	60%	
Literature range (except matching <i>a la</i> Ñopo (2008))			3%	33%	

discriminatory component in the last 40 years (Madalozzo, 2010; Garcia et al., 2009; Giuberti and Menezes-Filho, 2005; Leme and Wajnman, 2000). However, similar evidence was not found in the period assessed in the present article, in which a six percent point fall from 1996 to 2004 was followed by stagnation around 13% or 14%, a pattern that, notwithstanding, finds parallel in the “plateau” time trend exhibited in XXI century USA as reported by Goldin (2014).

As argued by Goldin (2014), the wage gap is a summary of gender labour market differences, including mainly age, wage disparity within occupations, especially those paying higher wages, and time allocated to unpaid work (e.g., caring for children). Lower willingness of women to bargain and compete in the labour market is also reflected (Goldin, 2014). The persistent significance of the discriminatory wage gap here observed have to be thus seen as a symptom of a multi-dimensional gender inequality.

The heterogeneity found in the occupational dimension is paralleled by the study of Madalozzo and Artes (2017, Table 7), in which management occupations classified as male-dominated achieved a larger wage gap. Garcia et al. (2009) found a greater discriminatory component in professional occupations (white collar, including top management), compared to intermediate level personnel (in the corporate hierarchy) and blue collar workers.

Regarding the method, the exercise pursued is further proof that propensity score matching is able to detect a part of the sample in which common support prevails in a satisfactory proportion of covariates' distribution, thus avoiding biased gender comparison. Matching diagnostics were crucial for such result, especially covariate balance tests and graphical representation. The degree of comparability achieved in the reduced subsample, with 64% of men and women paired, paralleled previous studies based on matching (Ñopo, 2008; Meara et al., 2020).

5.2. Implications

Results show that notwithstanding the progress, especially notorious in the turn of the century, gender pay equality was still not a reality by the middle of the second decade of XXIst century in Brazil. The female gender remained “taxed” by discrimination in 12% of the labour income earned, even holding the same level of human capital, which may be also interpreted, as in Goldin (2014), as the size of the “penalty to be an women”. The market value of women's time was in fact even smaller once considered their disproportional contribution for unpaid housework. Such mismatch between women's marginal productivity and wage has inefficiency implications beyond the labour market and affects investment in education (Azmat and Petrongolo, 2014) and, consequently, technological progress and long-run growth (as endogenous growth models suggest, Romer, 2012, chap. 3). In this sense, it is particularly worrying the stagnation around 13% of the

wage gap from 2004 to 2015. A second reason why such trend deserves highlighting is its simultaneity with the recession started in 2014, which may work to interrupt or even reverse the gender equality reduction observed earlier (Mont'Alvao and Ribeiro, 2020).

A remark on how elimination of wage discrimination may be achieved is merited. Goldin (2014), based in a detailed analysis of the wage gap in the USA, argues that, for full gender equality to be achieved, there is no need for policy but only for corporate changes, with employers reducing incentives for temporal work patterns that are less compatible with women's unpaid tasks – i.e., reduce the wage penalty charged for larger flexibility. Thus with greater workplace and temporal flexibility (i.e., reduced demand for tasks such as, for instance, “being around for clients”), allowing more freedom for female employees to schedule working hours, women would achieve the same wage level as men. Such change in the “personnel economics” practiced by firms would, in the labour market of the USA, be more effective than a policy for equalization of gender participation across occupations (Goldin, 2014).

Whether Goldin's (2014) prospect applies to Brazil is an open question. Madalozzo and Artes (2017) observed relevant within-occupation wage gaps in Brazil in 2013, especially among engineers, a clear contradiction of the lower science-technology gap detected by Goldin (2014). Madalozzo and Artes (2017) also found that men received higher wages for working in female-dominated and in gender homogeneous occupations, albeit females received a higher wage in male-dominated occupations, and working day was also shorter for females. These evidences can be roughly interpreted as indication that women are penalized for time flexibility, which is reinforced by the 12% motherhood wage loss estimated by Villanueva and Lin (2020). Madalozzo (2010) observed that in 2007, female wage was below and above men's in, respectively 12 and 6 of a total of 21 occupations and also that occupation participation differences across gender did not necessarily reduce women's wages, which parallels Goldin's (2014) assessment. A main reason for Goldin's (2014) path to gender wage equality not applying to Brazil is the considerable share of informal employment, as also seen in other developing countries, which offers greater flexibility but generally for smaller remuneration and lower social protection (Berniell et al., 2019; Mont'Alvao and Ribeiro, 2020). Also worryingly, Mont'Alvao and Ribeiro (2020) found the unemployment likelihood of young women, aged 18 to 24, to be 32.2% higher than young men during the ongoing recession.

In summary, what can be argued, based on the results here obtained, is that there is need for further research on whether the closing of gender wage gap in Brazil is a task to be left for companies to spontaneously undertake by changing hiring criteria, or whether policy is needed.

5.3. Limitations

Ñopo (2008) observes that “not all males are comparable to all females”. The statement is consistent with the fact that the author, by accounting for four explanatory variables¹⁰ as a basis for matching, could not find comparable pairs for 40% of men and 35% of women. Similar limitations were detected by Meara et al. (2017) when estimating the discriminatory component for the North American labour market and by Rubin (2001) in an analysis of the effect of smoking on health-related expenditures.

Accordingly, in this paper, common support proved to be limited to individuals with a propensity score under 80%, resulting in the exclusion of 36% of the sample, 94% of the excluded being men (see Table 2 above).¹¹ To reveal the limits of common support is undoubtedly one of the comparative advantages of the matching method (Rubin, 2001), since this information is a measure of the effective generality of the analysis (Dehejia and Wahba, 2002), which is not provided by OBD, for example. Consequently, the generalization of the results obtained for the entire employed Brazilian population is subjected to intolerable error. It is reasonable to generalize only to the population subgroup whose probability of presenting typically male characteristics does not exceed 80%.

The limited comparability of men and women has economic foundations associated with the interdependence of multiple decisions taken before and during participation in the labour market (Meara et al., 2020). Altonji and Blank (1999) consider that discrimination as a whole (or rather, the exposure to it) influences future preferences and decisions, which leads to the perpetuation of discrimination, inevitably reaching the labour market. This effect is related both with the influence of family and tradition in the choice of a profession and also with the decision to invest in human capital. Meara et al. (2017) also argue that the study of gender discrimination is limited because “gender segregation (. . .) means that many women and many men are undertaking different roles which are not easy to directly compare”. According to the authors, differences in daily working hours, parenthood, participation in low-paid sectors (gender segregation), also make it difficult to compare men and women.

6. Conclusion

The size and time coverage of the micro dataset assembled and the accuracy of the analytical method employed in this paper remain unparalleled in published studies of gender wage gap in Brazil. Results achieved are also an important part of the contribution offered. They showed that, although not all women are comparable to men, female wage discrimination

¹⁰ Age, education, marital status and migratory condition.

¹¹ These two proportions are averages across the whole period.

was, during 1996 to 2015, statistically and practically relevant in the comparable subset of the population. Importantly, continuation of the “grand gender convergence” (Goldin, 2014) was challenged by stagnation of wage gap around 13% from 2004 to 2015. Regarding the method, it was attested the potential of matching both to measure the discriminatory component of the gender wage gap and to uncover the trade-off between the accuracy and generality of such measurement.

Results adhered to previous studies mainly in regards to the significance of gender wage discrimination, but not necessarily in terms of the time trend exhibited by such measure, which, instead of the flat pattern here estimated, followed, in previous analyses, a downward trend. This discrepancy is not explained by method, since the widely adopted OBD resulted in the same trend than propensity score matching. It may be explained by a difference in the years selected for study, since other papers generally consider two extreme years of a period, and here four years in between the extremes were accounted for. Whether the first approach was applied, i.e., only 1996 and 2015 were considered, a decrease would result. Also, the period after 2010 was scantily examined so far.

Future research may, in the policy front, focus on whether gender gap closing requires intervention and, if this is the case, on how to design efficient intervention. Methodologically, the application of alternative matching techniques, such as Nopo's (2008) algorithmic approach and Firpo's (2018) recentered influence functions, is a fruitful avenue to pursue. Economic experiments and improved theory are also needed for better informing mechanisms perpetuating gender inequality, especially in the highly informal labour markets of developing countries.

Declaration of interest

None.

Acknowledgments

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Appendix A. Appendix A Matching estimators applied

In what follows, only the essential about estimators is described, namely, formula and pairing procedure, due to their widespread adoption in previous studies. The references taken as basis can be consulted for further detail (Morgan and Winship, 2007, sections 4.3 and 4.4, StataCorp, 2013 and Becker and Ichino, 2002).

The general formula of the PS logit estimator is:

$$\hat{ATT}_{log} = \sum_{i \in T} \frac{\sum_{i=1}^N w_i (\hat{y}_{1i} - \hat{y}_{0i})}{\sum_{i=1}^N w_i}$$

$$\text{With } \hat{y}_{ti} = \begin{cases} y_i, & \text{if } D_i = t \\ \frac{\sum_{j \in \Omega(i)} w_j y_j}{\sum_{j \in \Omega(i)} w_j}, & \text{contrariwise} \end{cases}$$

With $\Omega(i)$ being the pair set of the i -th observation and w_j the frequency of the j -th observation. Letter “T” represents the treated group (males).

The PS kernel estimator, using Becker e Ichino's (2002) notation is:

$$\tau^K = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{j \in C} Y_j^C G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \right\}$$

With $G(\cdot)$ being the kernel function, h_n the bandwidth size and subscript “C” denotes the control group (females; see also e.q 4.16 in Morgan and Winship, 2007).

According with Becker and Ichino (2002), the kernel estimators matches all treatment observations with a weighted average of all controls with weights inversely proportional to the treatment-control difference in propensity score. Therefore, it is expected that kernel matching presents a smaller variability of differences across pairs (given that the entire control group is taken as a “pair”).

The NN estimator has the same formula as the PS logit and, in the same way, the weight (w_i) is the share of observations paired with the i -th observation. The difference with PS logit is that the paired observations are those not exceeding a (pre-fixed) threshold for the distance metric in vector norm form below (StataCorp, 2013, p.114–115, Grilli and Rampichini, 2011):

$$\|\mathbf{x}_i - \mathbf{x}_j\|_{\Gamma} = \left\{ (\mathbf{x}_i - \mathbf{x}_j)' \Gamma^{-1} (\mathbf{x}_i - \mathbf{x}_j) \right\}^{1/2}$$

With \mathbf{x} being the covariate (attribute) vector and “ Γ ” the Mahalanobis distance metric, such that the distance between the i -th and the j -th observations is directly proportional to differences of the corresponding levels of the covariates (StataCorp, 2013, p.114–115).

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