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The Probability Of Exiting The Labor Market And Its Effects On The Gender Earnings Gap: Evidence Of Statistical Discrimination In Brazil's Labor Market

Cassia Helena Marchon
Laboratory Of Organizational Intelligence, Department Of Management And Decision Support, Technological Institute Of Aeronautics, São José Dos Campos, Sp, Brazil.

Abstract
This paper examines the chances of men and women leaving the labor market and its effects on the gender earnings gap in Brazil. Using the Oaxaca-Blinder decomposition, the earnings differential is broken down into a component explained by differences in observable attributes (education, occupation, etc.) and a residual component. In addition to the usual attributes, the analysis includes a forecast of the probability of a person interrupting her/his labor market participation. The PNAD—a nationally representative survey in Brazil—tracks its participants over five consecutive quarters. For each person working at the time of the first visit, the survey indicates whether she/he exits or remains in the labor market in subsequent visits. This information, along with the worker characteristics that are observable to those demanding labor, and stable over the work relationship, is used in a logit model to estimate the probability of a worker to exit the labor market. In the first quarter of 2024, men's average earnings surpassed women's by 19.4%, with the portion of the earnings gap explained by differences in attributes shifting from -3.1 to 17.5 percentage points after including the probability estimate. The results highlight the relevance of statistical discrimination practices in the labor market, i.e., discrimination based on historical data of different groups. Therefore, initiatives that facilitate women's retention in the labor market, such as access to care-related services, could promote greater gender earnings equity.
Keywords: *earnings gap; discrimination; Oaxaca-Blinder decomposition; labor market attachment; interruption in labor market participation; probability of exiting the labor market; Heckman; RIF*

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I. Introduction

Part of the earnings differential between men and women can be explained by differences in the average attributes between genders, such as the average number of hours each gender dedicates to the labor market. Another part may arise from unequal treatment in the labor market, which rewards the same attribute differently depending on whether the worker is a man or a woman. A widely used tool to disaggregate these two components is the Oaxaca-Blinder decomposition.

Considering the differences in average observable attributes between genders (years of education, occupation, experience, etc.), typically, studies for Brazil find that women's earnings should be higher than men's (Urquidi, Chalup, Sardán, 2023; Passos and Machado, 2022; Cirino, 2021; Pereira and de Oliveira, 2016; Matos and Machado, 2006; Scorzafave and Pazello, 2008). Thus, unless there are differences in relevant characteristics not accounted for in these studies, the earnings differential would result from discriminatory practices in the labor market. This study aims to better understand the origins of this discrimination and finds evidence that it consists, in great part, of statistical discrimination, i.e., discrimination based on the historical averages of a group.

Women in Brazil are over three times more likely than men to interrupt their participation in the labor market. Given that exits from the labor market can represent a cost to employers, coworkers, supervisors, business partners, contractors, etc., it is plausible that these agents practice statistical discrimination against women, similarly to insurance companies, which charge higher premiums for certain profiles of insured people.

CONSAD (2009) and Stein, Sulzbach, and Bartels (2015) attempt to capture the effect of potential career interruptions by using as a proxy the percentage of people outside the labor market for different age groups, gender and number of children. However, this approach is unnecessary when using panel data, as we can directly track the labor supply of the people in the sample over time. After all, people who have never entered the labor market do not represent a cost to those who demand labor. The problem lies in the interruptions in the professional trajectory. Moreover, people age and may have children over the course of an employment relationship, and those who demand labor are likely aware of this.

The present study uses data from PNAD—a nationally representative Brazilian panel—to observe whether individuals who were working during a given survey visit exited or remained in the labor market in subsequent visits. The probability of a worker to exit the labor market is estimated from the perspective of those demanding labor; thus, considering worker and work characteristics observable by them. It is also acknowledged that the probability of a worker to exit the labor market in the future does not depend solely on their current circumstances, which may change throughout the work relationship, such as the birth of a child or the aging of parents and in-laws. Therefore, this probability is estimated based on worker characteristics that tend to remain relatively stable over the course of the work relationship, such as industry sector, location, and education level. The equations are estimated by logit regressions and are subsequently applied to each worker to infer their likelihood of exiting the labor market.

We conclude that a significant part of the earnings differential results from the practice of statistical discrimination in the labor market. The significance of this probability of exiting the labor market appears to hold among poorer workers and in models that apply to the entire population, not just those currently employed. Therefore, effective policies aimed at reducing the differential would involve actions to reduce the need for women to leave the labor market.

The results highlight the relevance of this probability in explaining the gender earnings gap in Brazil. In the first quarter of 2024, the earnings gap between men and women was 19.4%. Once I include the probability of exiting the labor market as an explanatory variable, 17.5 percentage points of this gap can be explained by differences in average observed attributes between genders. In contrast, without this variable, the explained portion of the gap was negative at 3.1 percentage points. This suggests that a significant portion of the earnings gap results from the practice of statistical discrimination in the labor market. The relevance of the probability of leaving the labor market seems to hold true among the poorest workers and in models focused on the entire population, not just those working. Therefore, effective policies directed at reducing the gap would involve actions aimed at reducing the need for women to leave the labor market.

The study begins with a discussion on the probability of a worker discontinuing her/his participation in the labor market and the methodology used to estimate it. Following this, Mincerian equations explaining the earnings of men and women are estimated. Using these estimates, the Oaxaca-Blinder decomposition is calculated. Finally, the estimates are replicated for a Heckman sample selection model, and for the poorest quintile of the labor income distribution following the methodology proposed by Firpo, Fortin, and Lemieux (2018).

II. Probability Of Exiting The Labor Market

Worker adherence to the labor market is typically perceived as a positive attribute by employers, colleagues, supervisors, business partners, contractors, and others. Not knowing if a worker will leave the labor market in the future, those demanding labor might consider the typical behavior of various worker profiles within their respective industry. This is a common approach among insurance companies, which charge different premiums for different groups of individuals based on the historical data of each group. This practice is known as statistical discrimination.

It is possible to infer historical labor market exit rates for different profiles of workers and work using PNAD data. The PNAD is designed to visit each household in its sample for five consecutive quarters. Each quarter, approximately one-fifth of the households complete their fifth visit, are then removed from the sample, and new households are selected, ensuring constant sample renewal. During the period a household remains in the sample, it is possible to track the labor supply of its members. Particularly, it can be observed if a person was working during one visit but exited the labor market in a subsequent visit, meaning she/he was neither working nor seeking work.

Specifically, a dummy variable is constructed that takes the value 1 if an individual is working during a given visit but is out of the labor market in a subsequent visit for well-defined reasons. The reasons are: the need to take care of housework, children, or other relatives, being in school, health issues, or pregnancy. The dummy variable takes the value 0 if the person is in the labor market during a given visit and does not exit in a subsequent visit for any of the listed reasons.

The probability of a worker exiting the labor market is calculated from the perspective of those demanding labor, i.e., those in a position to practice statistical discrimination. Thus, it will be estimated based on worker characteristics that can be observed by them. It is also assumed that this probability can vary across business sectors and locations, and that each person on the demand side has information about their specific context. Additionally, it is acknowledged that the probability of a worker leaving the labor market in the future does not depend solely on their current circumstances. For example, a worker may not have children or elderly parents requiring her/his time at the present, but this may change in the future.

For simplicity, here the probability of a worker leaving the labor market depends on worker and work characteristics that meet two criteria: (i) they are easily observable by those demanding labor, and (ii) they tend to remain stable throughout the work relationship. Specifically, I assume that this probability depends on the worker's gender and education level, the industry sector in which the work relationship takes place, the region of the country where this relationship occurs, and whether it is in an urban or rural area.[1]

Indeed, 8.9% of women working in the first quarter of 2023 exited the labor market at some subsequent point for one of the aforementioned reasons. This figure surpasses the corresponding rate for men by more than threefold, which stands at 2.8%. Table 1, at the end of this text, presents the percentage of men and women who left the labor market for different worker and work characteristics. For informational purposes, the table includes characteristics that may change over the course of the employment relationship and that are not necessarily observable from the demand side.

The probability of a worker profile in a certain type of work exiting the labor market is estimated in a logit model. All estimations consider people between the ages of 18 and 55 to avoid issues related to retirement and compulsory schooling. In all the estimations presented in this work, the complexities of the PNAD sample design are considered. I use the econometric package Stata, with a highlight to the command svy for complex samples.

The results of the regression for the first quarter of 2023 and the preceding four quarters are presented in Table 2. The results reveal that women are more likely to exit the labor market than men, possibly reflecting the distinct realities and social roles associated with each gender. Moreover, workers are more likely to exit the labor market if they are: (i) less educated, (ii) in rural areas, (iii) in the north or northeastern regions of the country, and (iv) working in agriculture, livestock farming, forestry, fishing, aquaculture, domestic services, accommodation, food services, construction, and other services. It is worth noting that the results may reflect inequalities in conditions and opportunities.

The probability of a worker exiting the labor market is estimated as follows. First, the worker and work characteristics are inserted into the estimated equation for a given quarter. This provides the predicted probability of their exit according to the coefficients estimated for that quarter. This procedure is repeated for a total of 4 preceding quarters. Next, the average of the predicted probabilities over these four quarters is calculated. This averaging mitigates the effects of eventual seasonal and temporary fluctuations. The selection of the 4 preceding quarters happens with a lag to ensure that for each person considered in the logistic regression, it has already been determined whether they exited the labor market in some subsequent visit. The premise is that, at any given time t, those demanding labor use only the information available up to time t, not information that will emerge in the future. Since, in any given quarter t, there are individuals on their first visit, a year will pass before they complete their 5th and final visit. Therefore, the lag must be at least 1 year. For example, for each person in the 1st quarter of 2024, we take the average of her/his predicted probabilities according to the coefficients estimated in the logit regressions for the first quarter of 2023, the fourth, third, and second quarters of 2022.

In the next section, this averaged predicted probability is used as one of the explanatory variables in the equation explaining the earnings of men and women.

III. Mincerian Earnings Equation For Men And Women

Numerous studies estimate the so-called Mincer equation (1958) or Mincerian earnings equation. In this equation, labor earnings depend on observable characteristics, such as educational level, occupation, experience, etc. In studies on gender earnings gap that execute the Oaxaca-Blinder decomposition, a Mincerian equation is estimated for each gender as an introductory step for subsequent analyses.

Table 3 presents the explanatory variables considered in the present study, along with their respective regression coefficients. The first pair of columns shows the coefficients for men's regression and the second pair for women's. A novel aspect here is that the explanatory variables include the probability of a worker exiting the labor market, estimated based on worker and work characteristics observable by those who demand labor and that tend to remain constant throughout the work relationship, as detailed in the previous section.

For comparison purposes, Column (A) in the table presents the results when the estimated probability of exiting the labor market is not included among the explanatory variables. In (B), this probability is included. Generally, the other estimated coefficients exhibit similar patterns in estimations (A) and (B).

IV. Decomposition Of The Earnings Gap

The earnings differential between men and women and its decomposition into a differential explained by differences in average attributes between genders and a differential not explained by these differences, i.e., the so-called Oaxaca-Blinder decomposition (Oaxaca 1973; Blinder 1973), are presented in Table 4. The table also shows the contribution of each explanatory variable to the explained and unexplained differential.

In the first quarter of 2024, men's labor earnings surpassed those of women by 19.4%. In Column (A) of Table 4, the probability of leaving the labor market is disregarded. In this case, the explained differential stands

[1] Dummy variables for metropolitan areas and non-white people were not statistically significant in some of the regressions considered and were removed from the set of explanatory variables of the probability of labor market exit.

at -3.1 percentage points, meaning that based on average differences in observable attributes between genders, women's average earnings are expected to exceed those of men. This finding is consistent with other empirical studies for Brazil, such as those by Urquidi, Chalup, and Sardán (2023); Passos and Machado (2022); Cirino (2021); Pereira and de Oliveira (2016); Matos and Machado (2006); and Scorzafave and Pazello (2008).

However, when an estimate of the probability of a person leaving the labor market is included among the explanatory variables – Column (B) in Table 4 – differences in the means of the explanatory variables between men and women then explain 17.5 percentage points of the gender earnings differential. By itself, the estimated probability of leaving the labor market accounts for 19.2 percentage points of the explained earnings gap. Overall, the contribution of the remaining variables to the explained differential follows similar patterns in both estimations (Columns A and B).

To facilitate the analysis of the results, Columns (B) from Tables 3 and 4 are reproduced in Table 5. The first column presents the regression coefficients for men, and the second for women. The next two columns present the means of each variable for men and women, respectively.

Note that the market compensates men's and women's attributes differently, which contributes to the disparity in labor earnings between genders. Simultaneously, there are differences in the mean attributes between men and women that would lead to an earnings differential even if both were equally compensated for those attributes.

Consider, for example, the number of hours worked. Possibly, as a way to balance work outside the labor market, women dedicate fewer hours to the labor market than men, 38.29 hours compared to 42.19 hours. If women could dedicate the same number of hours as men to the labor market and received the same return per hour worked as men (0.015), the gender earnings gap would reduce by 5.9 percentage points ((42.19–38.29).0.015). This number is presented in the 5th column of Table 5, under the title Decomposition, subtitle Explained. On the other hand, each additional hour raises men's earnings by 1.5%, and women's by 1.7%. This difference in returns helps reduce the gender earnings gap by 7.7 percentage points ((0.015–0.017).38.29). This number is presented in the 6th column.

An analogous analysis applies to each explanatory variable, except for the categorical variables, which undergo a normalization process to ensure that the results do not depend on the choice of the omitted category (or reference category). The procedure is outlined in Jann (2008).

In the last pair of columns in Table 5, some variables are grouped into categories. For example, the heavier hours load of men—measured in terms of total working hours and the percentage working part-time—explains 8.6 percentage points of the earnings differential between men and women. Meanwhile, women's higher return for their hours load helps reduce the earnings differential by 8.7 percentage points.

Notably, with the exception of categories somehow related to the time dedicated to the labor market—hours load, experience (current job experience and its square, age and age squared), and probability of leaving the labor market—the average characteristics of women contribute to reducing the earnings differential. Consider, for instance, education. Women study 1.2 years more than men, on average. Taking men's return on education as a reference, women's higher education helps reduce the gender earnings differential by 4.7 percentage points.

Similarly, the distribution of women among the considered occupations would contribute to reducing the earnings differential by 3.7 percentage points if they received the same returns as men in each occupation. However, they tend to earn less than men in different occupations, which leads to a gender earnings gap of 2 percentage points.

Likewise, the distribution of women among the considered employment categories (employees with no official registration, employers, self-employed, and public sector) contributes to reducing the differential by 1.3 percentage points. However, unfavorable remuneration for women in different categories elevates the differential by 1.5 percentage points. Specifically, women are overrepresented among employees with no official registration, and they are more heavily penalized for this than men. Additionally, women are underrepresented among employers. Conversely, women are underrepresented among the self-employed. Lastly, women are strongly overrepresented in the public sector, which tends to reward those who succeed in its selection processes.

Among those in the labor market, the predicted probability of a typical woman leaving the labor market surpass that of a man by more than three times. This higher probability explains 19.2 percentage points of the gender earnings differential. On the other hand, men seem to be more penalized than women for characteristics that increase their probability of exiting the labor market, which helps reduce the earnings gap by 16.5 percentage points. This latter finding may perhaps represent a certain resistance of the labor market to changes in traditional social roles and possibly reinforces them.

Nevertheless, the detailed results should be observed with some caution, given the difficulty of isolating the individual effect of each variable when the variables are correlated. Table 6 displays the correlations between the variables for men (above the diagonal of the matrix) and for women (below the diagonal). Notice that the very estimated probability of leaving the labor market is, by design, strongly correlated with years of education. The inclusion of correlated variables is sometimes appropriate as a control or when the focus lies on more aggregated results.

A second caveat is that age may be a more accurate proxy for labor market experience among men, due to fewer interruptions in their labor market participation.

Lastly, the calculation of bootstrap standard errors for complex samples did not change the decomposition table, except for the unexplained differential for the North and South regions. The North moved from a 1% significance level to 5%, and the South from 5% to 10%.

V. Sample Selection Bias

The previous results refer to people with work. However, about 38.9% of women and 18.4% of men aged 18 to 55 were not working in the first quarter of 2024. This section aims to provide insights into the results for the entire population, including men and women without work. For this purpose, I use a Heckman (1979) sample selection model in which the probability of a woman (man) being working depends on her (his) age, education, if resides in an urban area, marital status, and whether she (he) has young children. The results are presented in Table 7 (first-stage regressions) and Table 8 (decomposition).[2]

Once including the probability of leaving the labor market among the explanatory variables, the share of the earnings differential explained by differences in average observable attributes rises to dominate the unexplained portion. Precisely, the ratio between the explained portion and the unexplained portion goes from approximately -0.16 to 1.19.

VI. Decomposition Among The Poorest

Lastly, the Oaxaca-Blinder decomposition is estimated among those with the lowest earnings. Specifically, I consider those in the first quintile of the labor earnings distribution. For this, I employ a statistical tool called recentered influence functions (RIFs). RIFs, originally useful in analyses involving outliers, gained popularity after their use by Firpo, Fortin, and Lemieux (2009) for estimating partial effects in the case of non-linear statistics. Firpo, Fortin, and Lemieux (2018) focus on the specific case of the Oaxaca-Blinder decomposition.

The method provides a linear approximation of non-linear functions, thus, approximation errors can occur (Rothe, 2010). On the other hand, alternative methods involving sequential decompositions do not allow identifying the effect of each variable independently of the order in which the decomposition is performed.

The commands used are detailed in Rios-Avila (2020) and Kolenikov (2010). The results for the first quintile of the earnings distribution are presented in Table 9.

In the context of this method, the equivalent of the earnings differential explained by differences in average attributes between genders is called the composition effect, while the unexplained differential is called the structure effect. When the probability of leaving the labor market is included among the explanatory variables, the composition effect increases and comes to dominate the structure effect. Specifically, the ratio between the composition effect and the structure effect changes from approximately 0.12 to 1.39 in absolute value.

VII. Final Remarks

In the first quarter of 2024, men's earnings surpassed women's by 19.4%. After including a forecast of the probability of a person leaving the labor market among the explanatory variables, the portion of the earnings differential explained by differences in average observable attributes jumped from -3.1 to 17.5 percentage points. This result suggests that the practice of statistical discrimination by those demanding labor is an important factor in explaining the gender earnings gap in Brazil. Additional analyses involving sample bias correction and poorer workers are also consistent with this conclusion.

The merit of identifying the nature of discrimination and its origins lies exclusively in its usefulness as a subsidy in formulating effective responses to the issue and, evidently, not as a justification for discrimination. In this regard, it is worth considering the practical implications of statistical discrimination within the scope of this work. A woman may receive a lower salary than a man with similar characteristics simply because she belongs to a group with a higher probability of leaving the labor market, even if she remains in the labor market throughout her economically active years.

It is estimated that approximately 9% of women left the labor market last year, compared to only 3% of men. It is important to note that, in isolation, pregnancies cannot explain this high percentage of women leaving the labor market. According to the IBGE, in 2022, about 2.4 million babies were born to mothers over 17 years

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[2] Using bootstrap standard errors for complex samples, the statistical significance of the unexplained portion of the differential changes from 1% to 5%. The unexplained differential attributed to the variables years of education and age lose statistical significance at the 10% significance level, while the significance level for age squared changes from 1% to 5%.

old in Brazil. In that same year, the female population aged 18 to 55 was approximately 60.8 million. This means, women who gave birth represent less than 4% of women in this age group. Moreover, not all women who give birth leave the labor market. It is therefore conjectured that other social impositions might be driving women out of the labor market, such as the need to care for parents, in-laws, spouses, and children beyond the immediate post-partum period. In this sense, public and institutional policies that enable women to remain working may involve the provision of a wide range of caregiving services, as well as incentives for a greater participation of men in these activities.

It is important to note that the tool employed, the Oaxaca decomposition, focuses exclusively on discrimination present within the labor market, and does not encompass discrimination that occurs before entering this market or in other social spheres. However, even within the scope of the labor market, this tool has its limitations. For instance, the over-representation of women among employees with no official registration may, at least in part, reflect discriminatory practices in the labor market that hinder women's access to better jobs. Additionally, it is possible that women occupy lower-paying jobs, anticipating the barriers and difficulties posed by the labor market to their gender in higher-paying employment. Furthermore, women's productivity might be affected by a less inclusive and motivating work environment, where they encounter fewer incentives and promotion opportunities, or even permissive of more explicit discriminatory practices, like harassment. Despite its limitations, the method may help identify the main factors that contribute to the gender pay gap and provide input for more effective actions to reduce this inequality.

Finally, it is necessary, still, to investigate the robustness of the results using different methodologies to estimate the probability of a worker leaving the labor market. Future research could explore alternative, more sophisticated, refined, and comprehensive approaches. For instance, considering, in certain cases, the worker's experience in their current work in order to better capture her/his circumstances at the time she/he started this work. Furthermore, the analysis could also incorporate other potential sources of statistical discrimination, such as temporary leaves of absence.

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