CAMILA RAFAELA ALVARENGA

THE GENDER GAP IN STEM: EVIDENCE FROM BRAZIL

Thesis submitted to the Applied Economics Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Doctor Scientiae*.

Adviser: Ian Michael Trotter

Co-adviser: Lorena Vieira da Costa Lelis

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Assent:

Camila Rafaela Alvarenga
Author

Ian Michael Trotter
Adviser

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To all my loved ones. You know who you are.

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ABSTRACT

ALVARENGA, Camila Rafaela, D.Sc., Universidade Federal de Viçosa, September, 2020. **The gender gap in STEM: evidence from Brazil**. Adviser: Ian Michael Trotter. Co-adviser: Lorena Vieira da Costa Lelis.

In Brazil, as in much of the world, women are underrepresented in STEM (Science, Technology, Engineering and Mathematics) majors, despite being the majority of students enrolled in tertiary education. Conversely, in primary and secondary education there exists a gender divide – favoring males – manifested in average gender differences in mathematical achievement. In order to uncover the structure of the gender gap in mathematics and establish a channel to the gender gap in STEM majors enrollment, we develop two essays. The first essay addresses the differences in mathematical achievement in primary and secondary education with an emphasis on the unexplained part of the gap. The main result is that most of the math-gender gap is explained by non-observable gender differences in the returns to individual, family and school characteristics, such that those difference in returns increase with school grade. The second essay addresses the matter of implicit gender stereotypes in the context in tertiary education. Among other things, we find that women in STEM are less likely to make stereotypical associations of the type, compared to women in humanities. With the aid of the literature on gender roles and stereotypes, our research results demonstrate that the subscription of individuals to gender-conforming educational paths, such as the school-grade increasing underachievement of girls in mathematics, (compared to boys), may inform the underrepresentation of women in STEM and, consequently, the gender differences observed in the labor market.

Keywords: Economics.Education.Gender.

RESUMO

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No Brasil, assim como em grande parte do mundo, mulheres estão pouco representadas nos cursos superiores de CTEM (Ciência, Tecnologia, Engenharia e Matemática). Similarmente, na educação primária e secundária existe uma divisão de gênero – favorencendo meninos e homens – que se manifesta em diferenças de gênero no desempenho em matemática. Com o objetivo de investigar a estrutura do *gap* de gênero em matemática e estabelecer um canal com o *gap* de gênero na representação em CTEM, são realizados dois ensaios. O primeiro ensaio adereça as diferenças de gênero no desempenho matemático na educação primária e secundária, com ênfase na parte não explicada do *gap*. O principal resultado é de que a maior parte do *gap* de gênero em matemática é explicado por diferenças de gênero não observáveis nos retornos às características individuais, familiares e escolares, de modo que as diferenças de retorno aumentam com a série escolar. O segundo ensaio adereça a questão dos estereótipos implícitos de gênero no contexto da educação superior. Entre outras coisas, observa-se que mulheres em cursos de exatas são menos propensas a apresentar associações estereotípicas do tipo *STEM é um campo masculino*, comparadas a mulheres das ciências humanas. Com auxílio da literatura sobre papéis e estereótipos de gênero, a pesquisa demonstra que a inscrição de indivíduos em trajetórias educacionais em conformidade com os papéis de gênero, como o desempenho médio inferior de meninas em matemática (comparadas a meninos) crescente na série educacional, informa a sub-representação de mulheres em CTEM e, consequentemente, as diferenças de gênero no mercado de trabalho.

Palavras-chave: Economia. Educação. Gênero.

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1 INTRODUCTION

Around the world, the formal education divide between genders has been on a closing trajectory. Only a few decades ago, men occupied the vast majority of student chairs in colleges and universities, and boys possessed a higher enrollment rate in primary education, compared to women and girls. However, as the enrollment rate in primary, secondary and tertiary education grew around the globe (ROSER; ORTIZ-OSPINA, 2013), so did the proportion of formally educated girls and women. This trend has been a steep one, such that nowadays women represent most of the students pursuing a higher education degree (United Nations Educational, Scientific and Cultural Organization (UNESCO), 2020).

As with any aspect of inequality, particularly gender inequality, what we observe is not linear or universal – in certain countries from the global south, such as the Philippines, gender differences in education have closed to the point of reversing (PAQUEO; ORBETA, 2019), while in others, such as Pakistan, girls still lag far behind boys in school enrollment (ROSER; ORTIZ-OSPINA, 2013). The heterogeneity in the global south is significant on this matter – according to the Gender Gap Index (GGI) (World Economic Forum, 2019), the Philippines ranks among the top 20 most gender equal countries in the world, while Pakistan occupies one of the last positions among 153 countries. On that note, it has been argued that countries that are less gender equal are more prone to gender differences in school achievement, particularly in mathematics (GUISO et al., 2008; ROMAN; RICA, 2016). Interrelated, these differentials are more common in countries where there are stronger gender stereotypes associating math and sciences with male traits (NOSEK et al., 2009). Consequently, this mechanism tends to reinforce the under-representation of women in the field of Science, Technology, Engineering and Math (STEM) (BHARADWAJ et al., 2016), despite being the majority of tertiary students.

In Brazil, a country that ranks in the ninety-second position of the GGI (World Economic Forum, 2019), far behind its neighbors Argentina, Colombia and Bolivia, mathematics is a challenge in and of itself, since Brazil has one of the worst overall math achievements according to the Programme for International Student Assessment (PISA) (Organisation for Economic Co-operation and Development (OECD), 2018). Furthermore, among Brazilian 15-year old students we observe a gender differential – a math gender gap – in disfavor of girls, comparable in size to that of Panama and the United Kingdom (Organisation for Economic Co-operation and Development (OECD), 2018).

Knowing that the math gender gap is associated with the gender gap in STEM and, therefore, with gender inequality in the labor market (ALTONJI; BLOM; MEGHIR, 2012; BHARADWAJ et al., 2016), and that there exists significant heterogeneity in education between global south countries, it is important to understand, on a country basis, the structure of the math gender gap, in order to draw specific policy designs to counter gender differences in career choices and the wage gap in Brazil.

Several studies have been conducted on the math gender gap, and also on the gender gap in STEM, as we will see in the subsequent chapters of this thesis. In Brazil, specifically, Arruda (2002), Palermo, Silva and Novellino (2014), Andrade, Franco and Carvalho (2016) have found a significant difference in average achievement, with boys outperforming girls, at different ages and school grades. However, to the best of our knowledge, no investigation of Brazil has analysed the gap at different points of the math achievement distribution, neither have they decomposed the gap into observable and unobservable parts. This is the first contribution of this research, and it is an important one. As Sohn (2012) indicates, if observable factors do not generally account for the entirety of the gap – and that often is the case – it is policy-relevant to explore the realm of non-observable factors.

The underlying hypothesis here is that the gender gap in mathematical achievement in Brazil is not explained by observed characteristics and it relates to societal attitudes towards women, affecting women's identification with math and their insertion in STEM fields. In order to assess that hypothesis, we divide our analysis into two essays, each addressing two specific objectives.

In the first essay, we investigate how the gender gap measured by math achievement behaves in different educational levels and in different points of the distribution, and we analyse the significance of subjective factors that might be associated with inferior average female achievement in math. With that, we aim to uncover structural elements of the gender gap, and evaluate if subjective factors such as societal views of women and gender stereotypes could be at the bottom of the gender gap.

In the second essay, we explore the matter of gender stereotyping by investigating the existence of the gender-STEM stereotype at Universidade Federal de Viçosa, in Southeastern Brazil, by means of a social experiment. Moreover, we analyse if stereotypical views of women are negatively correlated with the choice of math-intensive majors by women at the university. Through that examination, we aim to evaluate if implicit stereotypes are possibly affecting women's identification with math and their insertion in STEM fields. As we have reviewed above, the achievement and maintenance of a level playing field for men and women is beneficial from an economic perspective, additionally to being a desirable goal in itself, from a feminist perspective.

Other authors have conducted experiments such as this in other countries, as we will see in the second essay. For the most part, those were investigations of developed economies, in culturally diverse settings. We depart from these analyses by adapting the experiment to the realities of Brazil and by proposing a categorical analysis of the results, unlike other researches we have encountered.

The remainder of this work is organized as follows. First, we begin with the essay on the math gender gap in math achievement. Then, we follow with the research on gender-STEM stereotype. Finally, we present the concluding remarks.

2 NEW EVIDENCES ON THE GENDER GAP IN MATHEMATICAL ACHIEVEMENT IN BRAZIL

2.1 Initial remarks

South American countries have some of the worst overall achievement scores in math, according to the Programme for International Student Assessment (PISA) (Organisation for Economic Co-operation and Development (OECD), 2018). The average score in Brazil is below that of OECD countries, although it has been trending positive in the last decade. Among the subject areas tested by PISA – reading, mathematics and science – for Brazilian 15 year old students math is the subject with the lower relative score, similar to that of neighbor countries Argentina and Colombia.

PISA has consistently showed that, in Brazil, girls outperform boys in reading and, to a lesser extent, that boys outperform girls in mathematics. That is also the case of most of OECD countries and partners. The average gender difference in math achievement found in Brazil is similar to that of United States and Portugal in PISA 2018 (-9 points), although these countries are in a higher score category. Pondering the gender gap for average overall scores, the Brazilian gap is more similar in size to countries such as Panama and the United Kingdom (Organisation for Economic Co-operation and Development (OECD), 2018).

Several studies about the gender gap in math achievement were conducted in other countries: in a Fryer and Levitt (2010), in the United States, concluded that "girls are losing ground in math in every region of the country, every racial group, all levels of the socioeconomic distribution, every family structure, and in both public and private schools". In Chile, Bharadwaj et al. (2016) found that the average math gender gap increases with age. More recently, in Italy, Contini, Tommaso and Mendolia (2017) demonstrated that girls systematically under-perform boys and that the differential is larger among top performing children. In Kenya, Ng'ang'a, Mureithi and Wambugu (2018) reported that boys outperform girls in math in both public and private schools.

In Brazil, (ARRUDA, 2002) points that gender differences in math achievement are higher in the lower part of the socioeconomic status distribution. Pinto and Carvalho (2004) conclude that the gap in mathematical achievement is slightly significant and increasing in school grade. Finally, Andrade, Franco and Carvalho (2016) controlled for socioeconomic index, school-grade failure and child labor and found that boys consistently outperform girls in the same schools, on average.

A vast literature on the role of gender equity measures in the math gender gap has emerged in the last decades. Most of the studies are situated in the areas of psychology, sociology and education, oftentimes in an interface with economics.

In this context, the gender stratification hypothesis, proposed by Baker and Jones (1993), states that "socialization follows social structure", and so, that gender differences in opportunity supported by society can affect mathematical achievement and attitudes. Gevrek, Gevrek and Neumeier (2020) tested that hypothesis using a sample of 56 countries and concluded that "greater gender equity in access to tertiary education and lower gender wage gap are significantly associated with a smaller unexplained part of the gender math gap favoring boys, as proposed by the gender stratification hypothesis". Accordingly, Kane and Mertz (2012) argue that there exists a strong relationship between the math gender gap and measures of gender equity in the labor market, such as the gender wage gap and the rate of participation of women in the labor force. Similarly, Guiso et al. (2008) found that "the gender gap in math, although it historically favors boys, disappears in more gender-equal societies". Moreover, Marks (2008) observed that countries that have successfully implemented educational policies to improve the outcomes of girls do not display a significant math gender gap. In a social-psychological approach, Nosek et al. (2009) concluded, in a cross-country analysis, that implicit gender stereotypes are highly correlated with gender differences in math achievement[1].

In this sense, Greenwald and Banaji (1995) provided a framework establishing gender stereotypes as a predictor of the stronger association of male characters with achievement, in relation to female ones. This framework supported a host of experiment-based studies that went on to elaborate that in certain situations, women do not perform as well as men when they are tested – especially in math-related subjects – for reasons ranging from family background to low self-esteem, and the internalization of socially constructed gender stereotypes (DUFLO, 2012).

Outside the context of experimental or cross-country studies, it is difficult to observe the relationship between gender differences in math achievement and culturally established gender inequality and/or internalization of gender stereotypes. However, it is possible to account for the part of unobservable characteristics of a given group of individuals that are attributable to gender differences. A recent exploration of this perspective has been applied in other countries.

In an effort to explore the math gender gap using country-specific survey data, studies such as Sohn (2012), Gevrek and Seiberlich (2014) performed their versions of an inequality decomposition of the gender differences. They decomposed the gap into

[1] The details and definitions are situated in the next Chapter.

observable and unobservable parts, and found that, in the United States, there are distribution-specif gaps varying with age, that girls at the bottom of the distribution tend to get worse with age, and that non-observable factors account for most of the gap (SOHN, 2012). On the other hand, in Turkey the gender gap in math is statistically significant only in the upper part of the distribution, indicating that, only among top performing students, boys perform better than girls. Moreover, they find that boys are "better able to convert educational inputs into higher mathematics test scores", but that there is no gender difference in the return to individual and family characteristics (GEVREK; SEIBERLICH, 2014). To the best of our knowledge, no work on the area was conducted for a South American country.

The present study aims to demonstrate that gender plays a decisive role in the gender difference in math achievement that favors boys in Brazil – a country that ranks towards the bottom section of the Gender Gap Index (World Economic Forum, 2019). We perform a decomposition of the math gender gap into observable and unobservable parts, such that, in the latter element, we are able to measure which proportion can be attributed to actual gender differences in converting individual and contextual characteristics into math achievement. With this approach, we are able to identify gender-specific effects that can operate through differences in achievement in an unequal society.

2.2 Literature review

There exists a substantial literature on school achievement and the factors associated with it, in particular math achievement. However, there does not seem to exist a consensus about the channels through which gender differences in school achievement operate. This is likely due to the fact that there are as many subjective aspects linked to performance in school as there are objective and measurable factors. In this section, we review some of the evidence about the factors that may determine gender gaps in school achievement, which will, in turn, be the basis for our variable choice in the next section.

As parents are responsible for the early choices of education of their children – constrained by their wealth and income situation – and also pass on family values and beliefs, the educational outcomes of children and the schooling decisions made by young adults are contingent on parental investment (ALTONJI; BLOM; MEGHIR, 2012). Along with investment, parental educational attainment may indirectly affect such outcomes and decisions, given that there exists a clear correlation between students educational level and the one of their parents, mainly their mothers (DUFLO, 2012). Furthermore, research over the last decades has suggested the existence of a strong association between mother's schooling and child development, and thus, the existence of a significant predictive power of student achievement in mathematics as measured by standardized tests (CUI; LIU; ZHAO, 2019). Additionally, inter-generational transmission of gender role attitudes, especially from mothers to daughters, have been associated with the performance of girls in school, specifically in math. Interestingly, the same was not observed for boys (ROMAN; RICA, 2016).

Variables of the school environment, such as school socioeconomic status and teacher characteristics, have a significant impact on educational attainment (BHARADWAJ et al., 2016). There seems to exist a significant effect of professor gender on the math and science performance of female students, but not on that of male students (CARRELL; PAGE; WEST, 2010), with the gender gap being larger among high-performing students (CARRELL; PAGE; WEST, 2010; NOSEK; BANAJI; GREENWALD, 2002). An important finding is that the gender gap seems to disappear when outstanding female students take introductory classes with female professors (CARRELL; PAGE; WEST, 2010). Another school environment aspect that relates to the achievement gap between men and women is competitiveness among students – Niederle and Vesterlund (2010) concluded that the wish to avoid competition partially explains why women achieve less than men when they take a test.

Within the field of experimental psychology, it has been demonstrated that girls' attitudes[2], confidence and competitiveness in math are an important factor in their mathematical achievement (LIPPMANN; SENIK, 2018). In the same line, Dobarro and Brito (2010) states that the self-efficacy beliefs[3] of a student strongly influences his performance when solving math problems, in all levels of ability. Moreover, measures of math-anxiety have been successful in explaining part of the gender gap in math (CHEEMA; GALLUZZO, 2013; MIER; SCHLEEPEN; BERG, 2019).

An intriguing feature of the math-gender gap is that it seems to be more salient in and after adolescence, while at earlier ages boys and girls have about the same performance in math (HYDE; FENNEMA; LAMON, 1990; OSTI; MARTINELLI, 2014). More recently, in Chile Bharadwaj et al. (2016) did find a gender gap for children aged 9 and 10 years, although they found that the gap is twice as large for adolescents aged 13 and 14. In the United States, Fryer and Levitt (2010) found a similar pattern – the math-gender gap is not apparent in earlier grades, but by the end of the sixth year of school, girls under-perform in math, relative to boys. Moreover, Sohn (2012) points out that a consensus does not exist in regard to the relevance of the gender gap in math – some researchers conclude that the gender gap is trivial, and thus with little impact in higher education, while others recognize lasting effects of such gender differences.

[2] In this context, attitude is a predisposition for a situation, object or fact, and not an observable behavior (DOBARRO; BRITO, 2010)

[3] According to Dobarro and Brito (2010), mathematical self-efficacy belief is the confidence an individual possesses about his or her ability to successfully solve a math task.

Like age and school-grade, other characteristics may confound the size and significance of the gender gap. It has been demonstrated that differences in achievement by gender are more pronounced in high-performing samples of students (NOSEK; BANAJI; GREENWALD, 2002), such that mean measures of the gap may not yield relevant interpretations for policy. Moreover, evidence suggests that teachers tend to be more supportive of girls than boys in the school environment, and that boys are more likely to be in revision classes and to fail at school (PINTO; CARVALHO, 2004; GREGORIADIS; TSIGILIS, 2008). This raises the importance of integrating confounding characteristics such as school-grade failure into the analysis.

Similarly, Muñoz (2018) suggests that the math gender gap may be explained by sample selection caused by "gender differences in schooling's opportunity costs, which lead lower-achieving males to drop out". The author estimates that these differences account for 50 to 60 percent of the gender gap in Colombia. In Brazil, Andrade, Franco and Carvalho (2016) states that boys in lower socioeconomic settings are more likely to drop out from school, compared to girls. Therefore, this may be a possible source of bias in the context of this research, and it makes it even more important to look at gender differences at different parts of the distribution of math scores.

2.3 Identification strategy

Addressing causal effects for gender gaps is a tricky task since the disparities between boys and girls are an artifact of a range of observable and unobservable factors. The latter are particularly difficult to assess, given that societal phenomena such as gender stereotypes are difficult to measure and they vary with regional cultural norms and impact different individuals in different ways. So it is important to account for individual heterogeneity.

In this sense, Oaxaca (1973) and Blinder (1973) proposed a method to decompose the observable and unobservable effects of a variable in a given outcome. The method proposed allows us to observe the average difference in an outcome for two groups, such as:

$$R = E_i[Y_g] - E[Y_b] \tag{2.3.1}$$

where $E[Y_i]$ corresponds to the expected value of the score for the i (i=g, b) groups of girls (g) and boys (b) and its predictors. Considering the linear model:

$$Y_i = X\beta_i + \epsilon_i \tag{2.3.2}$$

It is possible to estimate the counterfactual of girls in the probability of presenting boys characteristics considering the estimated coefficients in:

$$Y_g - Y_b = [X_b'(\beta_g - \beta_b)] + [(X_g' - X_b')\beta_g] \tag{2.3.3}$$

Specifically, as explained by Fortin, Lemieux and Firpo (2011), let D_i represent a dummy for the student's gender, and taking the expectations over X, the overall score gap can be represent by:

$$\Delta_O^\mu = \mathbb{E}[Y_g|D_g = 1] - \mathbb{E}[Y_b|D_g = 0] \tag{2.3.4}$$

$$= \mathbb{E}[\mathbb{E}(Y_g|X, D_g = 1)|D_g = 1] - \mathbb{E}[\mathbb{E}(Y_b|X, D_g = 0)|D_g = 0] \tag{2.3.5}$$

$$= (\mathbb{E}[X|D_g = 1]\beta_g + \mathbb{E}[\epsilon_g|D_g = 1]) - \mathbb{E}[X|D_g = 0]\beta_b + \mathbb{E}[\epsilon_b|D_g = 0]) \tag{2.3.6}$$

where $\mathbb{E}[\epsilon_g|D_g = 1]) = \mathbb{E}[\epsilon_b|D_g = 0] = 0$. Adding and subtracting the average counterfactual score that girls would take under the characteristics of boys, $\mathbb{E}[X|D_g = 1]\beta_b$, the expression becomes:

$$\Delta_O^\mu = \mathbb{E}[X|D_g = 1]\beta_g - \mathbb{E}[X|D_g = 1]\beta_b + \mathbb{E}[X|D_g = 1]\beta_b - \mathbb{E}[X|D_g = 0]\beta_b \tag{2.3.7}$$

$$= \mathbb{E}[X|D_g = 1](\beta_g - \beta_b) + (\mathbb{E}[X|D_g = 1] - \mathbb{E}[X|D_g = 0])\beta_b \tag{2.3.8}$$

$$= \Delta_S^\mu + \Delta_X^\mu \tag{2.3.9}$$

Simply, replacing the expected values of the covariates by the sample averages, the decomposition can be estimated such as:

$$\hat{\Delta}_O^\mu = \bar{X}_g\hat{\beta}_g - \bar{X}_g\hat{\beta}_b + \bar{X}_g\hat{\beta}_b - \bar{X}_b\hat{\beta}_b \tag{2.3.10}$$

$$= \bar{X}_g(\hat{\beta}_g - \hat{\beta}_g) + (\bar{X}_g - \bar{X}_b)\hat{\beta}_b) \tag{2.3.11}$$

$$= \hat{\Delta}_S^\mu + \hat{\Delta}_X^\mu \tag{2.3.12}$$

In the above equation, $\hat{\Delta}_S^\mu$ are the *gender-return effects* and $\hat{\Delta}_X^\mu$ are the *composition effects*. The gender-return effects are the main interest here. It represents the effect of being female on the average math score of the group, compared to males. As described by Sohn (2012), it is "attributable to the fact that girls have the same characteristics as boys but the effects of the characteristics are different from those of boys". On the other hand, the composition effect is a result from the fact that boys and girls have different characteristics (composition).

To observe the effects in different parts of the distribution of math scores, we approach this problem from a quantile regression framework. Sohn (2012) and Gevrek and Seiberlich (2014) found differences in test scores that were systematically different throughout the distribution. Specifically, Sohn (2012) found that there are quantile-specific gaps across the distribution of math achievement in the United States, and that the size of the gap varies with age. In Turkey, Gevrek and Seiberlich (2014) also observe an heterogeneous pattern in the gender gap in math achievement across the distribution.

In this sense, the quantile regressions procedure provides a pragmatic approach to observe the differential impacts of covariates along the distribution outcome. The classical framework - Conditional Quantile Regressions (CQR) - proposed by Koenker and Jr (1978) is limited in a sense that effects are conditional to a covariate and it is not possible to generalize the effects of a specific variable to the whole distribution. Namely, differently from OLS models, $Q_\tau(Y_i|X_i) = X_i'\beta_\tau$, does not imply in $Q_\tau(Y_i) = Q_\tau(X_i')\beta_\tau$. Therefore, to address the observable features that contributes to the disparities among boys and girls and also to see it in different levels of the distribution, Firpo, Fortin and Lemieux (2018) advanced in the quantiles analysis literature and proposed the so-called Unconditional Quantile Regression (UQR) method. This method allows estimate marginal effects of covariates in quantiles for any functional form, using the Recentered Influence Function (RIF):

$$RIF\,(Y; q_\tau) = q_\tau + \frac{\tau - \mathbb{I}\,\{Y \leq q_\tau\}}{f_Y(q_\tau)} \tag{2.3.13}$$

where $\mathbb{I}\,\{Y \leq q_\tau\}$ is an indicator function of the threshold values of the outcome variable - here the math scores - when it is less than or equal to quantile q_τ; $f_Y\,(q_\tau)$ represents the distribution density function of Y on the quantiles. From there, the interest effect can be describe as the Unconditional Quantile Partial Effect (UQPE) parameter to be estimated such as:

$$\alpha(\tau) = c_{1,\tau}[Y > q|X = x]dxdFX(x) \tag{2.3.14}$$

where $c_{1,\tau}$ is the density function $c_{1,\tau} = 1/f_Y(q_\tau)$.

Given these features, we estimate the gender differences in mathematics scores in different quantiles. Furthermore, we apply the Oaxaca-Blinder decomposition to separate observable and unobservable characteristics that explain possible gaps – composition and gender-return effects.

2.3.1 Database and variables

The dependent variable, *math score*, corresponds to the standardized math score of each student who completed the SAEB exam (details below). The explanatory variables were chosen based on the theoretical relevance of each factor in math achievement, on the use of variables on previous studies, as we have seen in the literature review, and in the univariate covariation between each variable and math achievement (PALERMO; SILVA; NOVELLINO, 2014). The variable descriptions are given in Table 1.

Table 1 – Variable descriptions.

Variable	Description
Math score	Math test score
Female	= 1 if student is female
Individual characteristics	
Black	= 1 if student is black
Age	Student's age
Flunked school	Sum of times student has failed a school year
Pre-school	= 1 if student has attended pre-school
Math homework	= 1 if student does math homework
Housework	Approximate weekly hours spent doing domestic work
Labor	= 1 if student works outside the household
Family background	
Mom's schooling	Approximate years of schooling of student's mother
Family size	Number of residents in the household
Socioeconomic status	Index of infrastructure and material goods in the household
Incentive	Index of incentive to study from parents
Reading habits	Index of reading habits of student and parents
School characteristics	
Female math teacher	= 1 if math teacher is female
Positive belief	= 1 if teacher holds a positive belief over class achievement
Aggression	Index of verbal and/or physical aggression in class
White weapon	= 1 if teacher has witnessed a white weapon during class
Socioeconomic status	Index of socioeconomic status of school
Federal school	= 1 if school is administered by the federal government
State school	= 1 if school is administered by the state government
Municipal school	= 1 if school is administered by the municipal government
Urban area	= 1 if school is located in an urban area
North	= 1 if school is in Northern Brazil
Northeast	= 1 if school is in Northeastern Brazil
Southeast	= 1 if school is in Southeastern Brazil
South	= 1 if school is in Southern Brazil
Central-West	= 1 if school is in Central-West region Brazil
N	Number of observations

We will use data from *Sistema Nacional de Avaliação da Educação Básica* (SAEB) from the year 2017 to conduct the analysis for Brazil. The SAEB database is produced biannually by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep/MEC) and consists of standardized tests and socio-economic questionnaires designed to evaluate the quality of education in Brazil. The tests are applied to students in fifth and ninth grades, and also to students concluding high school. The SAEB data is considered to be representative of the population given that sampling extends to all Brazilian territory and all schools and cities must have at least 50% of their students participating in the evaluation.

The math test in SAEB focuses on problem solving. It is designed according to the method of Incomplete Block Designs (IBD), which makes it possible to evaluate students according to the reference matrix of math without submitting individuals to an all-encompassing exam. For fifth grade students, 77 questions were divided among 7 blocks of 11 questions each, so that each student responds to 2 blocks totalling 22 questions. For ninth grade students, the scheme is the same but the number of questions *per* block is 13, so that each student answers 26 questions out of 91 (Instituto Nacional de Estudos e Pesquisas Educacionais Anisio Teixeira, 2016).

In addition to the test, each student receives a questionnaire (see Appendix **??**) to fill out, containing questions about the family environment and their socioeconomic situation, their school history and study habits. They also provide information about how motivated they feel to study, and how family and teachers contribute to that feeling.

Three other questionnaires are applied the same day – teachers and school directors are responsible for informing about their academic and professional background, leadership style, pedagogical and disciplinary practices and also about the school environment. Moreover, the technician visiting the school observes and reports about school infrastructure and resources, general environment, among other aspects[4].

2.3.2 Missing data approach

According to Vinha and Laros (2018), studies who use data from educational surveys in Brazil rarely report missing values. In the cases they did, the treatment applied was usually deletion of observations that were missing data[5]. For all variables tested for missing values in the sample, there was a difference in average math score between respondents and non-respondents. The pattern we found is that, on average, math score is higher in clusters of students who responded to the question that generated the tested variable[6]. It is also the case that the overwhelming majority of

[4] All questionnaires are available in Instituto Nacional de Estudos e Pesquisas Educacionais Anisio Teixeira (2016) micro data file online.

[5] See Vinha and Laros (2018) for a list of studies who reported missing data from education databases and their respective treatment strategies.

[6] After merging the student level database with class and school level data, we found that in classes and schools where the teacher/technician did not respond the questionnaire, students have lower mean

survey non-response (RUBIN, 1987) – partial or complete – is in the student questionnaire, and concentrated on the fifth grade.

It is significant that, after the first round of missing data deletion [7], 44,6% of fifth grade observations are missing information about the schooling of mother. Methods of imputation are a possible way to avoid selection bias, but in this case imputation may not be viable due to the fact that the imputed sample would be almost as big as the baseline sample. In the ninth and third (high school) grades the missing percentage is smaller – 22,6% and 8,8%, respectively. This significant proportion of survey non-response (especially in fifth grade) is unlikely to occur completely of random, so it is reasonable to assume that respondents and non-respondents are systematically different from each other. To test that hypothesis, we compared the mean math score of each group and found that the difference is not statistically different, even when controlling for gender, our variable of interest.

2.4 Results

2.4.1 Descriptive statistics

The descriptive statistics by gender of fifth, ninth and third grades are summarized in Tables 2, 3 and 4, respectively.

In fifth grade, Table 2 reveals that there is a higher proportion of boys, relative to girls, who are black, who works, and who have failed a school year. Moreover. Conversely, girls tend to do more domestic work, as well as math homework, and went to pre-school in a slightly higher proportion than boys. The difference in mean math score is small – slightly higher than 1 point – and statistically significant.

In ninth grade, as displayed in Table 3, we observe the same patterns of fifth grade. The variables in which the difference by gender are more pronounced are housework – girls do more domestic work than boys – and labor – a higher proportion of boys have a job, compared to girls. We also observe that the difference between genders is superior to 10 points. Observing the data in Table 4, we see that in high school the patterns are the same and that the gender gap reaches almost 13 points, the higher difference among grades. Figure 1 illustrates the distribution of math grades from male and female students of each grade.

Overall, male students reported a higher average in mother's education, as well as a higher socioeconomic index. Furthermore, female students reported receiving more

math scores, in comparison to those that responded.

[7] Observations were deleted based on non-response of the generating questions of variables *math_score, female, black, flunked, homework, NCS, age, fam_size, NCC, labor* and *pre_school*.

Table 2 – Descriptive statistics by gender – 5th grade.

	Full sample		Male		Female		
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	t-test
Math score	230.08	46.78	230.74	48.33	229.45	45.26	10.08
Female	0.51	0.50	0.00	0.00	1.00	0.00	-
Individual characteristics							
Black	0.10	0.30	0.11	0.32	0.09	0.29	29.54
Age	10.83	0.92	10.92	1.00	10.73	0.83	74.96
Flunked school	0.26	0.60	0.33	0.65	0.20	0.53	78.21
Pre-school	0.29	0.45	0.29	0.45	0.30	0.46	-9.11
Math homework	0.93	0.25	0.92	0.26	0.94	0.23	-25.77
Housework	1.58	1.20	1.49	1.20	1.66	1.19	-51.82
Labor	0.11	0.31	0.15	0.36	0.06	0.25	102.91
Family background							
Mom's schooling	9.13	5.09	9.16	5.19	9.10	4.99	3.72
Family size	4.26	1.20	4.26	1.21	4.26	1.19	-2.03
Socioeconomic status	10.13	4.27	10.26	4.34	10.00	4.20	21.59
Incentive	5.56	0.80	5.49	0.85	5.62	0.74	-55.76
Reading habits	2.68	0.62	2.64	0.65	2.71	0.58	-39.88
School characteristics							
Female math teacher	0.03	0.18	0.03	0.18	0.03	0.18	-1.42
Positive belief	1.49	0.64	1.48	0.65	1.50	0.64	-10.95
Aggression	0.39	0.49	0.39	0.49	0.39	0.49	4.04
White weapon	0.03	0.18	0.03	0.18	0.03	0.17	2.45
Socioeconomic status	3.38	0.89	3.38	0.90	3.38	0.89	-0.17
Federal school	0.00	0.03	0.00	0.03	0.00	0.03	-0.57
State school	0.21	0.41	0.21	0.40	0.21	0.41	-4.29
Municipal school	0.78	0.41	0.79	0.41	0.78	0.41	4.42
Urban area	0.91	0.28	0.91	0.28	0.91	0.28	-2.98
North	0.11	0.32	0.11	0.31	0.12	0.32	-4.88
Northeast	0.24	0.43	0.24	0.43	0.24	0.43	4.20
Southeast	0.42	0.49	0.42	0.49	0.42	0.49	-0.80
South	0.14	0.35	0.14	0.35	0.14	0.35	1.20
Central-West	0.09	0.28	0.09	0.28	0.09	0.28	-0.95
N	532291		259251		273040		

Note: The last column presents t-statistics for the difference in the means of the male and female samples.

Table 3 – Descriptive statistics by gender – 9th grade.

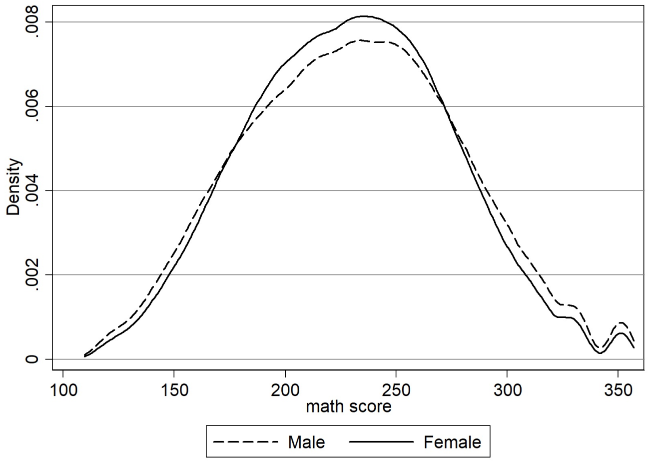
	Full sample		Male		Female		
Variable	Mean	S.D	Mean	S.D	Mean	S.D.	t-Test
Math score	258.17	48.09	263.85	49.77	253.38	46.09	78.69
Female	0.54	0.50	0.00	0.00	1.00	0.00	-
Individual characteristics							
Black	0.12	0.32	0.13	0.34	0.10	0.31	31.19
Age	14.88	0.98	14.98	1.03	14.80	0.93	67.34
Flunked school	0.34	0.61	0.43	0.67	0.27	0.55	91.27
Pre-school	0.42	0.49	0.40	0.49	0.44	0.50	-30.73
Math homework	0.94	0.23	0.94	0.25	0.95	0.21	-25.96
Housework	1.66	1.08	1.34	1.04	1.93	1.04	-200.00
Labor	0.13	0.34	0.19	0.39	0.08	0.28	112.00
Family background							
Mom's schooling	8.43	4.62	8.71	4.65	8.20	4.58	39.45
Family size	4.18	1.17	4.16	1.16	4.20	1.17	-13.62
Socioeconomic status	9.66	4.07	10.10	4.26	9.29	3.87	71.36
Incentive	5.46	0.89	5.43	0.91	5.49	0.87	-24.39
Reading habits	2.46	0.76	2.47	0.76	2.45	0.76	11.49
School characteristics							
Female math teacher	0.26	0.44	0.27	0.44	0.26	0.44	1.83
Positive belief	1.36	0.59	1.35	0.59	1.36	0.59	-6.24
Aggression	0.52	0.50	0.52	0.50	0.52	0.50	1.60
White weapon	0.06	0.25	0.06	0.25	0.06	0.25	0.08
Socioeconomic status	3.25	0.92	3.27	0.92	3.23	0.92	12.88
Federal school	0.00	0.05	0.00	0.05	0.00	0.04	0.94
State school	0.54	0.50	0.54	0.50	0.53	0.50	7.05
Municipal school	0.45	0.50	0.44	0.50	0.45	0.50	-7.83
Urban area	0.89	0.31	0.89	0.31	0.89	0.31	3.94
North	0.11	0.31	0.11	0.31	0.11	0.31	-1.25
Northeast	0.31	0.46	0.30	0.46	0.32	0.47	-14.35
Southeast	0.35	0.48	0.36	0.48	0.35	0.48	11.28
South	0.14	0.35	0.14	0.35	0.14	0.35	2.69
Central-West	0.08	0.27	0.08	0.28	0.08	0.27	2.57
N	519986		237796		282190		

Note: The last column presents t-statistics for the difference in the means of the male and female samples.

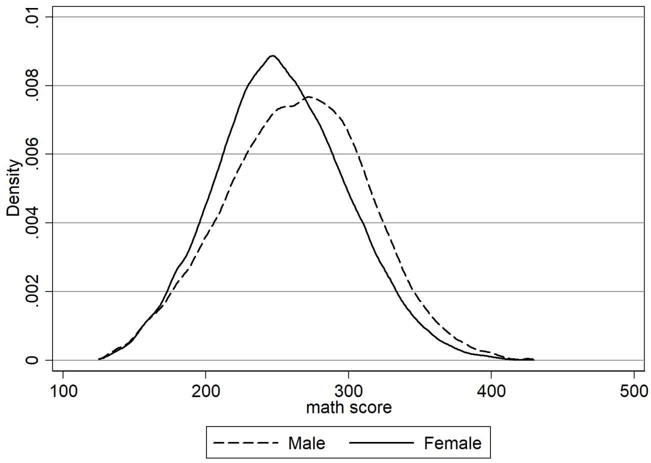
Table 4 – Descriptive statistics by gender – 3rd grade.

	Full sample		Male		Female		
Variable	Mean	S.D	Mean	S.D	Mean	S.D.	t-Test
Math score	280.01	59.48	287.17	62.20	274.28	56.56	38.11
Female	0.56	0.50	0.00	0.00	1.00	0.00	-
Individual characteristics							
Black	0.13	0.33	0.14	0.34	0.12	0.32	11.13
Age	17.71	1.08	17.77	1.08	17.66	1.07	17.83
Flunked school	0.37	0.67	0.43	0.70	0.32	0.64	28.25
Pre-school	0.38	0.49	0.37	0.48	0.38	0.49	-2.86
Math homework	0.83	0.37	0.83	0.38	0.84	0.37	-4.77
Housework	1.88	1.26	1.63	1.22	2.08	1.26	-63.35
Labor	0.24	0.43	0.29	0.45	0.20	0.40	37.57
Family background							
Mom's schooling	9.29	4.73	9.67	4.66	8.99	4.75	25.06
Family size	3.95	1.16	3.93	1.14	3.96	1.18	-4.49
Socioeconomic status	9.76	4.26	10.32	4.45	9.30	4.04	42.06
Incentive	5.18	1.09	5.11	1.13	5.23	1.05	-19.15
Reading habits	2.36	0.84	2.37	0.85	2.35	0.84	3.13
School characteristics							
Female math teacher	0.19	0.39	0.19	0.39	0.19	0.39	-1.27
Positive belief	1.47	0.55	1.48	0.55	1.47	0.55	3.19
Aggression	0.42	0.49	0.42	0.49	0.42	0.49	0.73
White weapon	0.06	0.23	0.06	0.23	0.06	0.23	0.72
Socioeconomic status	3.45	1.11	3.49	1.11	3.42	1.11	11.12
Federal school	0.03	0.18	0.04	0.19	0.03	0.17	6.93
State school	0.75	0.43	0.74	0.44	0.76	0.43	-6.80
Municipal school	0.00	0.07	0.00	0.07	0.00	0.07	-0.81
Urban area	0.97	0.16	0.97	0.16	0.98	0.16	-3.40
North	0.13	0.34	0.13	0.34	0.13	0.34	-0.29
Northeast	0.24	0.43	0.23	0.42	0.25	0.43	-6.89
Southeast	0.41	0.49	0.42	0.49	0.41	0.49	4.92
South	0.15	0.35	0.15	0.36	0.14	0.35	3.68
Central-West	0.07	0.26	0.07	0.25	0.07	0.26	-2.66
N	123737		55054		68683		

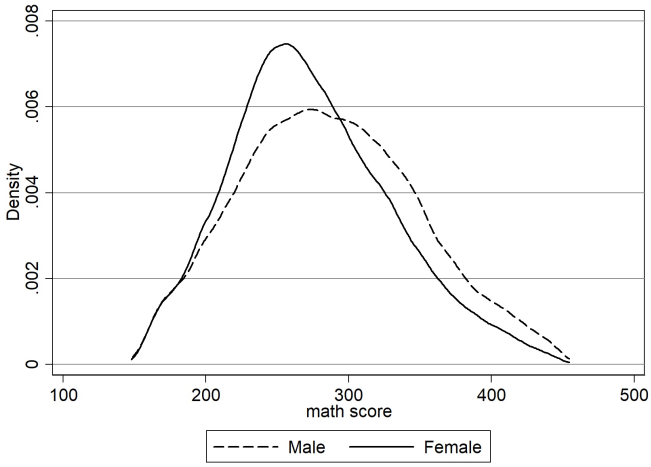
Note: The last column presents t-statistics for the difference in the means of the male and female samples.



(a) 5th grade.



(b) 9th grade.



(c) High school.

Figure 1 – The distribution of math achievement by gender.

incentive from parents in school matters. Other family characteristics – family size and family reading habits – presented variation in gender differences across grades.

The characteristics associated with the school (and the geographic location) vary less with gender. Generally, the majority of students and schools in the sample are located in urban areas and in states of the Northeast and Southeast regions. The schools are, on the most part, public. In fifth grade they consist mostly of municipal schools, in the ninth grade they are a mix of municipal and state schools, and in the third grade they are primarily state schools.

2.4.2 Unconditional quantile regression and Oaxaca-Blinder decomposition

In past years, researchers have found differences in math achievement between boys and girls in Brazil (ARRUDA, 2002; ANDRADE; FRANCO; CARVALHO, 2016), with boys performing better. Our results expand on these results by performing an analysis that permits for heterogeneity across the distribution of math grades and, subsequently, by decomposing the gender gap into an observable and an unobservable component.

Table 5 shows the gender gap in math achievement given by the unconditional quantile regression (UQR) for all three grades. We estimated four models for each grade. The baseline model is the model in which the only dependent variable is the *dummy* female, the individual characteristics model shows the coefficient of female after controls were added for individual characteristics. The family background model controls, additionally, for family characteristics. Finally, the last model shows the coefficient of the gender gap after controlling for all the variables, including school characteristics.

Overall, it is noticeable that the gender gap in math achievement is bigger in higher quantiles. The baseline model, that is, the model in which the only independent variable is the dummy *female*, gives the size of the math gender gap without controls. It is interesting to observe that, in fifth grade, the gender gap is reversed in the bottom quantiles, but it becomes negative (disfavoring girls) when controls are added. In the other grades, the gender gap exists in all quantiles, and it intensifies when controlling for individual characteristics. Another feature of the results is that the gender gap is bigger in the upper quantiles, above the median, compared to bottom quantiles.

The fact that controlling for individual characteristics – color, age, labor, school history – increases the gender gap across all quantiles and grades is interesting. It suggests that the features associated with girls reinforce their disadvantage to boys, instead of helping "explain" or reduce them. The full results are in Tables 6, 7 and 8 in the Apppendix, and they demonstrate that being black is associated to lower grades to an even higher degree than gender, particularly among younger students. Among older students, the gender factor plays out more significantly in terms of math achievement than color.

Furthermore, the results in Table 5 indicate that family background accounts for

Table 5 – Unconditional quantile regression results for fifth, ninth and third grades.

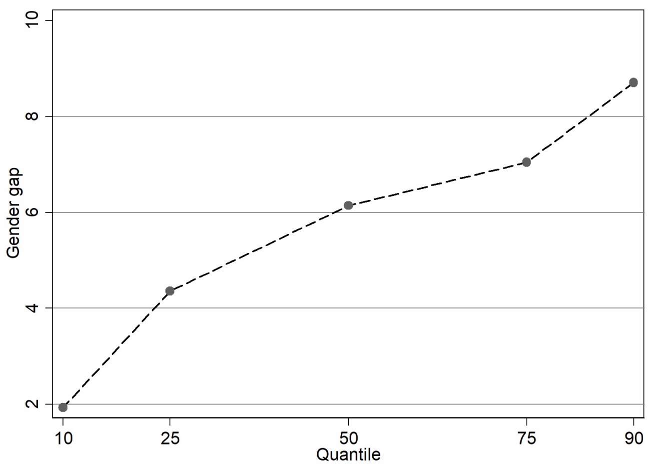
Model/Quantile	10%	25%	50%	75%	90%
Fifth grade					
Baseline	3.470***	1.443***	-1.281***	-3.644***	-6.045***
	(0.197)	(0.182)	(0.175)	(0.173)	(0.218)
Individual characteristics	-2.577***	-5.347***	-7.321***	-8.130***	-9.742***
	(0.193)	(0.174)	(0.168)	(0.172)	(0.222)
Family background	-2.236***	-4.767***	-6.587***	-7.415***	-9.036***
	(0.192)	(0.172)	(0.165)	(0.170)	(0.221)
School characteristics	-1.929***	-4.356***	-6.142***	-7.046***	-8.710***
	(0.189)	(0.168)	(0.161)	(0.167)	(0.219)
Ninth grade					
Baseline	-2.997***	-7.360***	-13.24***	-14.87***	-13.16***
	(0.223)	(0.178)	(0.174)	(0.189)	(0.235)
Individual characteristics	-8.123***	-12.74***	-18.93***	-20.07***	-17.63***
	(0.233)	(0.182)	(0.176)	(0.196)	(0.252)
Family background	-6.636***	-10.76***	-16.47***	-17.60***	-15.26***
	(0.233)	(0.181)	(0.176)	(0.195)	(0.252)
School characteristics	-6.784***	-10.91***	-16.66***	-17.84***	-15.61***
	(0.231)	(0.178)	(0.172)	(0.191)	(0.248)
Third grade (high school)					
Baseline	-1.650***	-6.745***	-15.81***	-20.19***	-19.88***
	(0.493)	(0.406)	(0.444)	(0.536)	(0.723)
Individual characteristics	-4.528***	-9.548***	-18.65***	-22.75***	-21.81***
	(0.492)	(0.398)	(0.431)	(0.530)	(0.736)
Family background	-2.931***	-7.102***	-14.21***	-16.04***	-13.06***
	(0.494)	(0.398)	(0.425)	(0.515)	(0.712)
School characteristics	-3.526***	-7.960***	-15.69***	-18.33***	-16.28***
	(0.492)	(0.390)	(0.403)	(0.468)	(0.652)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses.

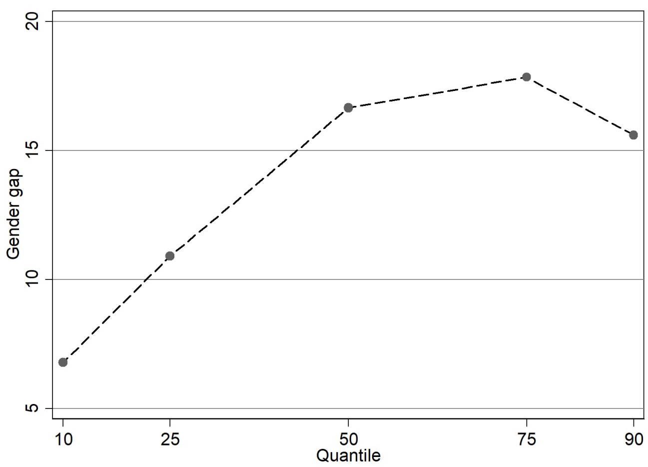
a small part of the gender gap among younger individuals, and to a bigger share of the gap among older students. This suggests that, the higher the grade/age, the higher the explanatory power of factors such as schooling of the mother, reading habits of the family and being given incentive to study in the gender gap.

The addition of school characteristics also yields heterogeneous effects on the gender gap across grades. What is more, it operates in different directions – in fifth grade, controlling for school characteristics contributes to reducing the gap, even if only marginally. On the other grades, adding these controls increases the gender gap, suggesting that girls are systematically inserted in school environments that accentuate their disadvantage to boys. The descriptive statistics (Table 4) as well as the extended results in the Appendix (Table 8) indicate that girls in high school attend schools with lower socioeconomic status than boys and, complementary, that girls are less represented in private schools.

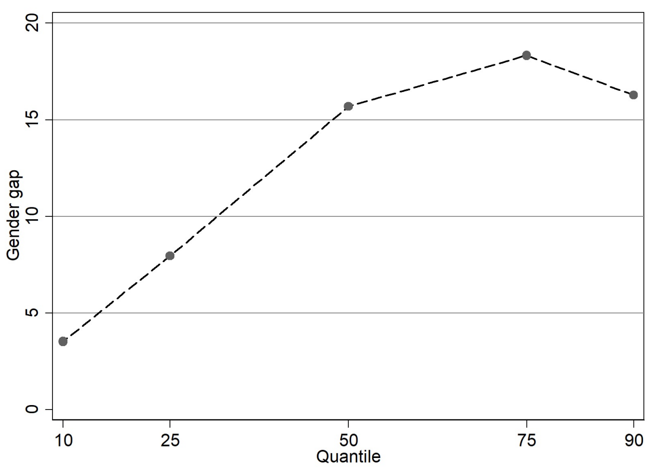
Another important finding is the fact that, even when controlling for individual, family and school characteristics, females in the upper quantiles perform worse relative to boys, when compared to the lower quantiles. Figure 2 illustrate the size and heterogeneity of the gender gap across quantiles and grades, after controlling for individual, family and school characteristics. We note that this quantile-specific analysis alleviates some of the bias arising from the drop out of low-achieving males, since the gender gap is robust at the top of the distribution, where the high achievers – are situated.



(a) 5th grade.



(b) 9th grade.



(c) High school.

Figure 2 – The gender gap in each quantile.

The results in Figure 2 support the argument that the gender gap in attainment measured by math grades increases for higher levels of education, such as indicated by

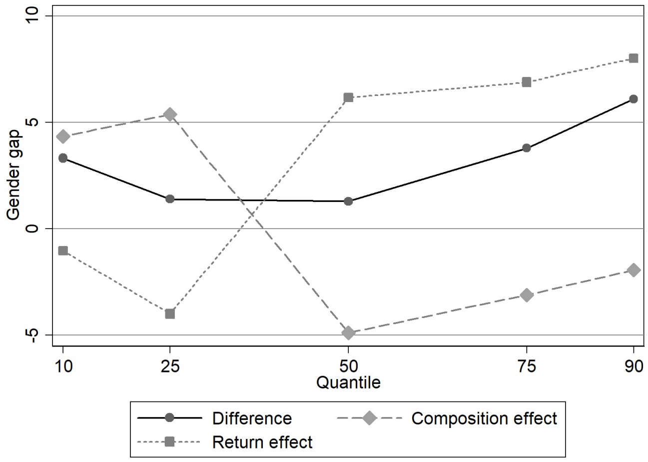
Hyde, Fennema and Lamon (1990), Fryer and Levitt (2010), Bharadwaj et al. (2016). Through all ages, the descriptive statistics indicate that boys represent most of black students, as well as most of the students who work and who failed a school year. Nonetheless, they systematically outperform girls in math tests, through all levels of achievement, after accounting for their observable characteristics and their social contexts.

To better understand these results, we then conduct the decomposition of the math-gender gap, by separating it into an observable part – the composition effect – and an unobservable one – the gender-return effect. The Oaxaca- Blinder decomposition results are illustrated in Figure 3 for each grade and quantile. The graphs are composed by three lines: composition effect, return effect and difference (between effects).

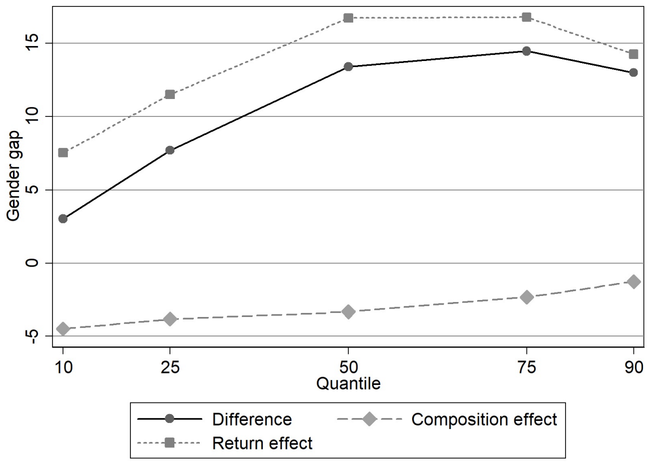
In fifth grade, Figure 3a, composition and gender-return effects vary in relative importance along the distribution of math achievement. In lower quantiles, the characteristics attributed to students and their contexts – that is, their composition – account for most of the gender gap, while in higher quantiles (50% and above) the returns to being male are preponderant. This means that, among high achievers, boys tend to be more successful in converting their features into math achievement than girls are.

In ninth grade (Figure 3b) and high school (Figure 3c), the decomposition of the gender gap tells a different story. Throughout the distribution, the unobservable features dominate over observable ones, such that the higher the quantile, the higher the returns to being male (with the exception of the last quantile, where we observe a small decline). Generally, we observe that bigger gender gaps are associated both with higher quantiles and with higher return effects to male students.

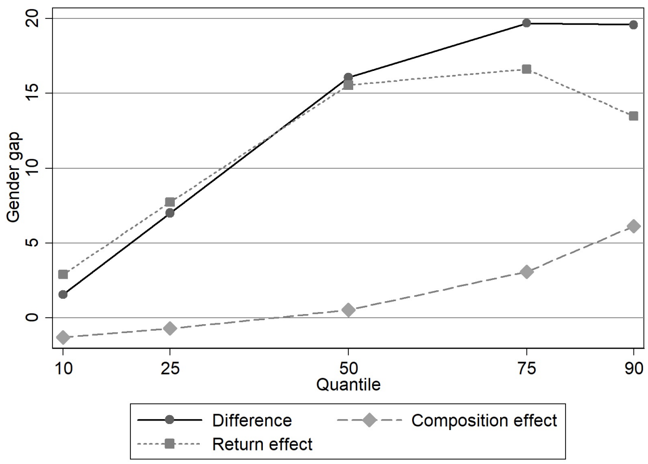
The pattern in Figure 3 suggests that the degree to which unobservable gender differences impact the gender gap in math achievement is increasing on age or school grade. In turn, this finding supports the argument that gender stereotypes are plausible predictors of gender differences, given that the sensitivity to stereotyping tends to increase with age (MARTIN; WOOD; LITTLE, 1990), as does the assimilation of gender roles (ALBERT; PORTER, 1988). Of course this exercise does not permit to single out the specific channels through which these differences operate, but it does allow for the understanding that subjective features and phenomena that operate through gender differences explain the gender gap in math.



(a) 5th grade.



(b) 9th grade.

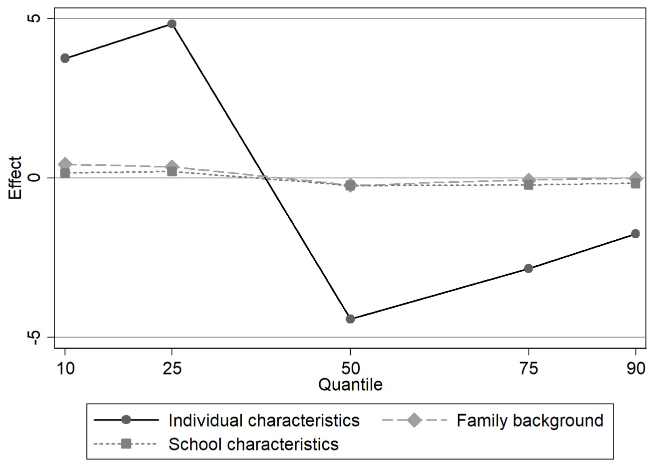


(c) High school.

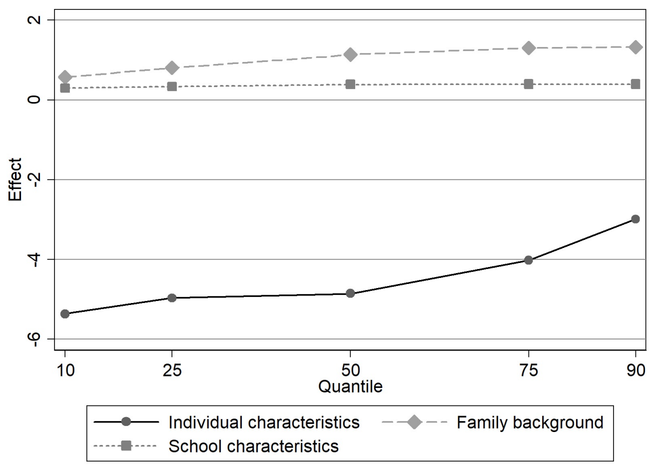
Figure 3 – OB decomposition of the gender gap in math.

In order to explore the dynamics of the effects, Figures 4 and 5 break the composition and gender-return effects, respectively, into three sets of characteristics:

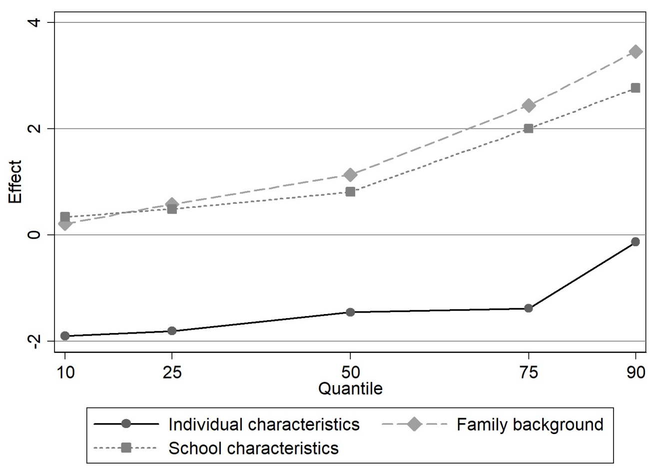
individual, family and school, following the same criteria of the UQR estimation above.



(a) 5th grade.



(b) 9th grade.



(c) High school.

Figure 4 – Composition effect of the gender gap in math.

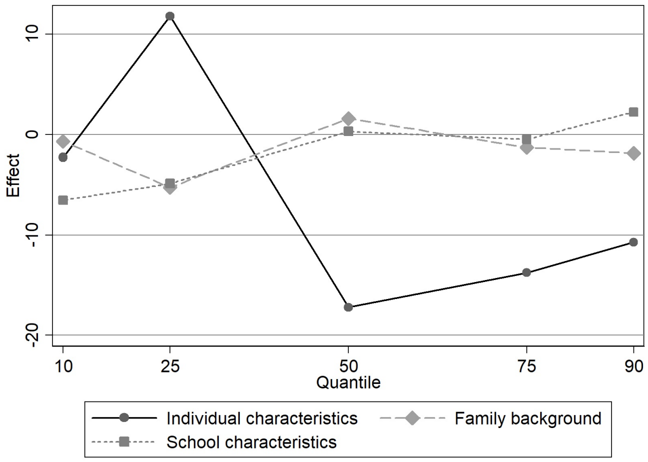
The structure of composition effects in Figure 4 varies with each grade. Among younger students (Figure 4a), school and family characteristics account for almost none of the gender gap, and the effect of individual features are mixed – in lower quantiles, the individual-based differences of boys and girls reinforce boys advantage in achievement, while at higher quantiles this logic is opposed. Note that, since familiy and school characteristics do not account for much of the composition effect, the trajectory of the individual characteristics line in Figure 4a is similar to that of the composition effect in Figure 3a.

In ninth grade (Figure 4b and high school (Figure 4c) the bulk of the composition effect is also attributed to the set of individual characteristics, but with a few differences. First, in both cases the effect of individual features increases in quantile. Second, there is some – if limited – contribution of family and school characteristics to the composition effect, also increasing in quantile. Overall, it can be argued that, at higher quantiles, actual differences in contextual characteristics contribute to explaining part of the gender gap in math. This is supported by the trajectory of the entire composition effect in Figure 3a, and it is especially true for high school students.

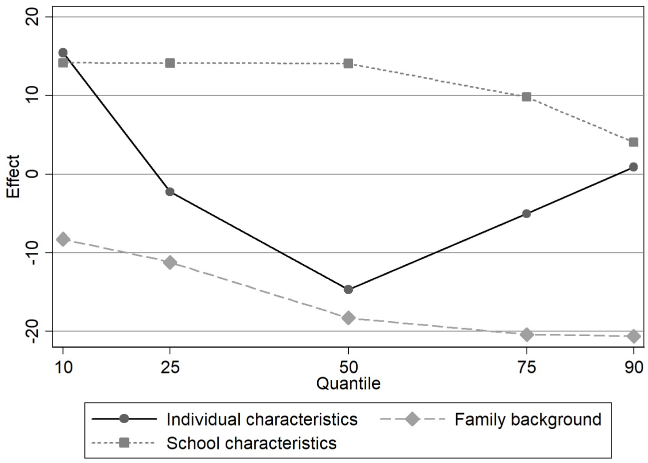
As for the structure of the gender-return effect, Figure 5 yields mixed returns from each set of characteristics. In fifth grade (Figure 5a), at the upper end of the distribution girls enjoy more returns than boys for their individual characteristics. A similar (but not so strong) pattern is observed in ninth grade (Figure 5b) but not in high school (Figure 5c). Thus, we observe that among students in upper quantiles, as males age they become increasingly better in converting their individual features into math achievement, relative to female students.

The gender-specific return to family characteristics has a undefined and hard to interpret trajectory in fifth grade, but in the others the pattern is well-defined, indicating a discernible gender difference in this context. In ninth and third grades (Figures 5b and 5c, respectively), the higher the level in the distribution, the more females are better able to convert their family input into math scores, relative to males. However, the size of this effect in not big enough to change the pattern of the gender-return effect as a whole. As seen in Figure 3, the overall result is that boys obtain more returns to their features and context than girls do, and the actual differences in composition do little in explaining the gender gap.

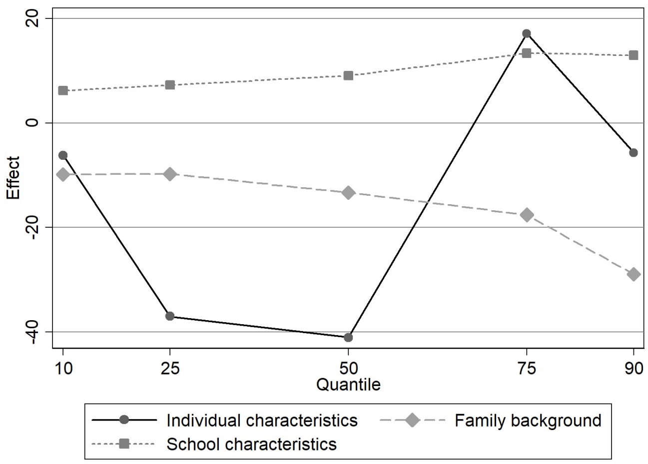
As for school characteristics, the patterns are less clear. What can be said is that, in ninth grade and high school (Figures 5b and 5c, respectively) the unobservable effects or returns to school inputs are favorable to girls, as opposed to boys, along all the distribution. All these results are expressed in numbers in Tables 9 and 10 in the Appendix.



(a) 5th grade.



(b) 9th grade.



(c) High school.

Figure 5 – Gender-return effect of the gender gap in math.

2.5 Concluding remarks

The objective of this study was to demonstrate that subjective features associated with gender are significant in the math-gender gap in Brazil. For this, we employed test results from Sistema de Avaliação da Educação Básica (SAEB) for the year of 2017, and analysed the performance of students in primary (fifth and ninth grade) and secondary (third grade) education. We performed an Oaxaca-Blinder decomposition of the math-gender gap in the context of a Unconditional Quantile Regression method.

The main challenge in the research was the fact that subjectivity happens within the realm of non-observable characteristics. The average gender differences we observe in mathematical achievement are partially a function of socially constructed gender roles and stereotypes, which may affect each individual in a different and specific way. Most importantly, it may affect certain group types – high and low performers, for example – in different and specific ways.

Nevertheless, we were able to demonstrate that gender differences in math achievement persist across primary and secondary education (increasing with school-grade), that they are not explained by individual, family and school characteristics and, finally, that most of the math-gender gap is explained by unobservable gender differences in the returns to these characteristics. Moreover, we found that among higher levels of schooling and higher math test performances, such gender inequalities are more salient.

These results support the argument that one of the ways that gender socialization operates is through the dis-identification of women with math, which in turn tends to reinforce the under-representation of women in the field of Science, Technology, Engineering and Math (STEM). In a wider sense, gender differences in math achievement may prevent girls from achieving their highest educational potential. They miss the opportunity of choosing from a wider range of careers and attaining the higher monetary returns associated with STEM careers. On the aggregate level, the math-gender gap is detrimental for competitiveness in the labor market and it perpetuates the culture of gender inequality in a very material sense.

In the interest of deepening the understanding of how gender stereotypes correlate with math-intensive majors in Brazil, in the next Chapter we analyse a social experiment conducted in a Brazilian university.

In future studies, we recommend that authors look at the intersection of gender with other relevant inequality features, particularly color and/or ethnicity.

2.A Appendix – Unconditional Quantile Regression results

Table 6 – Unconditional quantile regression extended results – 5th grade.

Variables	(2) 10%	(2) 25%	(2) 50%	(2) 75%	(2) 90%	(3) 10%	(3) 25%	(3) 50%	(3) 75%	(3) 90%	(4) 10%	(4) 25%	(4) 50%	(4) 75%	(4) 90%
Female	-2.577***	-5.347***	-7.321***	-8.130***	-9.742***	-2.236***	-4.767***	-6.587***	-7.415***	-9.036***	-1.929***	-4.356***	-6.142***	-7.046***	-8.710***
	(0.193)	(0.174)	(0.168)	(0.172)	(0.222)	(0.192)	(0.172)	(0.165)	(0.170)	(0.221)	(0.189)	(0.168)	(0.161)	(0.167)	(0.219)
Black	-15.66***	-18.95***	-19.00***	-15.57***	-13.46***	-13.51***	-16.29***	-16.32***	-13.30***	-11.42***	-12.49***	-14.74***	-14.37***	-11.41***	-9.547***
	(0.398)	(0.324)	(0.264)	(0.225)	(0.253)	(0.395)	(0.321)	(0.262)	(0.224)	(0.253)	(0.391)	(0.315)	(0.259)	(0.224)	(0.254)
Age	-6.109***	-6.252***	-5.148***	-3.411***	-2.616***	-4.762***	-4.645***	-3.551***	-2.066***	-1.394***	-3.683***	-3.171***	-1.913***	-0.649***	-0.0896
	(0.168)	(0.125)	(0.0968)	(0.0854)	(0.102)	(0.168)	(0.124)	(0.0965)	(0.0856)	(0.103)	(0.166)	(0.121)	(0.0947)	(0.0849)	(0.103)
Flunked school	-15.85***	-19.98***	-19.62***	-15.16***	-12.49***	-13.88***	-17.69***	-17.43***	-13.33***	-10.84***	-12.97***	-16.25***	-15.68***	-11.67***	-9.275***
	(0.262)	(0.201)	(0.148)	(0.117)	(0.128)	(0.260)	(0.200)	(0.148)	(0.118)	(0.128)	(0.258)	(0.196)	(0.147)	(0.118)	(0.128)
Pre-school	2.277***	4.327***	5.916***	5.930***	5.816***	2.879***	4.993***	6.555***	6.486***	6.360***	1.978***	3.504***	4.887***	5.149***	5.331***
	(0.201)	(0.184)	(0.182)	(0.190)	(0.247)	(0.200)	(0.182)	(0.179)	(0.188)	(0.246)	(0.203)	(0.183)	(0.179)	(0.188)	(0.247)
Math homework	17.16***	21.86***	21.88***	17.63***	14.64***	12.84***	16.86***	17.25***	13.96***	11.48***	10.07***	12.68***	12.56***	9.868***	7.770***
	(0.517)	(0.411)	(0.312)	(0.240)	(0.249)	(0.518)	(0.411)	(0.313)	(0.243)	(0.254)	(0.530)	(0.416)	(0.320)	(0.254)	(0.271)
Housework	-1.469***	-1.953***	-1.967***	-1.604***	-1.371***	-1.357***	-1.790***	-1.786***	-1.447***	-1.223***	-1.073***	-1.237***	-1.049***	-0.680***	-0.433***
	(0.0866)	(0.0763)	(0.0698)	(0.0672)	(0.0827)	(0.0859)	(0.0752)	(0.0687)	(0.0665)	(0.0822)	(0.0889)	(0.0763)	(0.0689)	(0.0669)	(0.0830)
Labor	-27.98***	-29.00***	-23.08***	-16.59***	-13.87***	-26.96***	-28.04***	-22.32***	-16.03***	-13.32***	-23.90***	-24.42***	-18.73***	-13.13***	-10.72***
	(0.432)	(0.331)	(0.257)	(0.219)	(0.252)	(0.428)	(0.326)	(0.254)	(0.219)	(0.254)	(0.421)	(0.318)	(0.249)	(0.217)	(0.253)
Mom's schooling						1.190***	1.327***	1.256***	1.086***	1.059***	0.974***	1.075***	0.989***	0.834***	0.807***
						(0.0213)	(0.0189)	(0.0173)	(0.0168)	(0.0209)	(0.0214)	(0.0188)	(0.0172)	(0.0168)	(0.0209)
Family size						-1.367***	-2.257***	-2.898***	-2.399***	-2.064***	-0.475***	-1.191***	-1.886***	-1.651***	-1.456***
						(0.0884)	(0.0753)	(0.0684)	(0.0662)	(0.0814)	(0.0878)	(0.0738)	(0.0672)	(0.0655)	(0.0812)
Socioeconomic status						0.928***	1.364***	1.513***	1.341***	1.181***	0.0956***	0.348***	0.507***	0.562***	0.521***
						(0.0251)	(0.0215)	(0.0201)	(0.0204)	(0.0262)	(0.0261)	(0.0219)	(0.0206)	(0.0211)	(0.0272)
Incentive						4.731***	5.032***	4.107***	2.943***	2.453***	4.109***	4.142***	3.094***	2.047***	1.613***
						(0.163)	(0.131)	(0.109)	(0.101)	(0.124)	(0.162)	(0.128)	(0.107)	(0.0996)	(0.123)
Reading habits						0.995***	0.183	-0.459***	-0.848***	-1.331***	0.993***	0.371**	-0.0709	-0.375***	-0.774***
						(0.184)	(0.157)	(0.143)	(0.141)	(0.179)	(0.182)	(0.153)	(0.140)	(0.139)	(0.179)
Urban area											7.097***	4.139***	-0.424	-3.211***	-5.218***
											(0.450)	(0.354)	(0.292)	(0.267)	(0.326)
Female math teacher											0.116	1.222***	1.109**	0.999**	1.979***
											(0.522)	(0.468)	(0.452)	(0.470)	(0.636)
Positive belief											2.819***	3.887***	4.373***	3.988***	3.812***
											(0.166)	(0.143)	(0.129)	(0.125)	(0.154)
Aggression											-1.507***	-2.084***	-2.919***	-3.436***	-4.043***
											(0.198)	(0.176)	(0.168)	(0.171)	(0.218)
White weapon											-2.044***	-2.842***	-3.201***	-2.483***	-2.666***
											(0.606)	(0.519)	(0.456)	(0.421)	(0.492)
Socioeconomic status											5.729***	7.061***	8.228***	8.476***	9.103***
											(0.151)	(0.133)	(0.131)	(0.139)	(0.188)
Federal school											-1.581	-0.449	6.587**	4.825	7.252
											(1.558)	(1.989)	(2.563)	(3.703)	(5.987)
State school											-0.0310	-5.987***	-13.40***	-16.75***	-18.59***
											(0.630)	(0.702)	(0.890)	(1.238)	(1.970)
Municipal school											0.113	-6.008***	-14.03***	-18.49***	-20.66***
											(0.618)	(0.692)	(0.882)	(1.230)	(1.959)
Constant	230.3***	258.0***	280.3***	295.8***	317.3***	174.9***	198.8***	229.5***	255.7***	282.7***	155.3***	180.6***	213.4***	236.8***	260.8***
	(1.865)	(1.398)	(1.092)	(0.962)	(1.147)	(2.108)	(1.597)	(1.275)	(1.143)	(1.380)	(2.370)	(1.931)	(1.777)	(1.917)	(2.670)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses.

Table 7 – Unconditional quantile regression extended results – 9th grade.

Variables	(2) 10%	(2) 25%	(2) 50%	(2) 75%	(2) 90%	(3) 10%	(3) 25%	(3) 50%	(3) 75%	(3) 90%	(4) 10%	(4) 25%	(4) 50%	(4) 75%	(4) 90%
Female	-8.123***	-12.74***	-18.93***	-20.07***	-17.63***	-6.636***	-10.76***	-16.47***	-17.60***	-15.26***	-6.784***	-10.91***	-16.66***	-17.84***	-15.61***
	(0.233)	(0.182)	(0.176)	(0.196)	(0.252)	(0.233)	(0.181)	(0.176)	(0.195)	(0.252)	(0.231)	(0.178)	(0.172)	(0.191)	(0.248)
Black	-8.546***	-9.416***	-11.17***	-11.86***	-11.81***	-7.617***	-8.172***	-9.624***	-10.35***	-10.39***	-6.800***	-7.299***	-8.572***	-9.217***	-9.260***
	(0.390)	(0.291)	(0.260)	(0.252)	(0.283)	(0.390)	(0.290)	(0.259)	(0.251)	(0.282)	(0.391)	(0.289)	(0.257)	(0.251)	(0.283)
Age	-9.120***	-7.821***	-6.673***	-5.252***	-3.921***	-7.826***	-6.179***	-4.667***	-3.226***	-1.925***	-7.605***	-5.758***	-4.088***	-2.602***	-1.343***
	(0.200)	(0.134)	(0.111)	(0.107)	(0.126)	(0.202)	(0.135)	(0.111)	(0.108)	(0.127)	(0.205)	(0.135)	(0.110)	(0.107)	(0.127)
Flunked school	-10.21***	-12.84***	-15.41***	-15.62***	-15.05***	-9.959***	-12.54***	-15.05***	-15.27***	-14.71***	-8.868***	-11.29***	-13.60***	-13.76***	-13.10***
	(0.308)	(0.217)	(0.183)	(0.170)	(0.189)	(0.307)	(0.215)	(0.180)	(0.169)	(0.188)	(0.308)	(0.214)	(0.178)	(0.167)	(0.186)
Pre-school	4.459***	5.033***	6.035***	6.222***	6.277***	4.699***	5.334***	6.406***	6.611***	6.666***	4.820***	5.418***	6.506***	6.787***	7.009***
	(0.219)	(0.174)	(0.170)	(0.185)	(0.233)	(0.219)	(0.172)	(0.167)	(0.182)	(0.232)	(0.219)	(0.171)	(0.165)	(0.180)	(0.229)
Math homework	14.98***	12.56***	11.21***	10.46***	10.70***	16.23***	14.49***	13.82***	13.25***	13.28***	17.15***	15.66***	15.05***	14.26***	14.04***
	(0.590)	(0.418)	(0.363)	(0.350)	(0.385)	(0.595)	(0.419)	(0.363)	(0.351)	(0.390)	(0.590)	(0.413)	(0.356)	(0.345)	(0.384)
Housework	1.287***	1.609***	1.773***	1.233***	0.409***	1.254***	1.549***	1.696***	1.157***	0.342***	0.823***	1.091***	1.314***	1.023***	0.512***
	(0.113)	(0.0863)	(0.0812)	(0.0849)	(0.103)	(0.113)	(0.0856)	(0.0801)	(0.0839)	(0.102)	(0.113)	(0.0847)	(0.0786)	(0.0826)	(0.101)
Labor	-4.276***	-3.143***	-2.850***	-3.196***	-3.981***	-5.028***	-4.236***	-4.261***	-4.613***	-5.293***	-5.176***	-4.422***	-4.340***	-4.400***	-4.608***
	(0.361)	(0.271)	(0.256)	(0.270)	(0.326)	(0.360)	(0.270)	(0.253)	(0.268)	(0.326)	(0.358)	(0.265)	(0.248)	(0.263)	(0.323)
Mom's schooling						0.930***	1.109***	1.348***	1.447***	1.501***	0.815***	0.981***	1.182***	1.231***	1.198***
						(0.0267)	(0.0205)	(0.0195)	(0.0209)	(0.0263)	(0.0273)	(0.0207)	(0.0196)	(0.0210)	(0.0264)
Family size						-1.580***	-2.316***	-2.795***	-2.263***	-1.775***	-0.303***	-0.842***	-1.208***	-0.847***	-0.538***
						(0.101)	(0.0774)	(0.0718)	(0.0736)	(0.0886)	(0.102)	(0.0772)	(0.0713)	(0.0734)	(0.0887)
Socioeconomic status						0.942***	1.280***	1.615***	1.597***	1.497***	0.0483	0.247***	0.474***	0.531***	0.507***
						(0.0294)	(0.0227)	(0.0222)	(0.0244)	(0.0312)	(0.0319)	(0.0242)	(0.0234)	(0.0257)	(0.0327)
Incentive						-0.421***	-1.254***	-1.861***	-2.044***	-1.762***	0.0613	-0.739***	-1.339***	-1.617***	-1.404***
						(0.151)	(0.112)	(0.105)	(0.114)	(0.147)	(0.150)	(0.110)	(0.103)	(0.112)	(0.144)
Reading habits						-2.080***	-2.094***	-2.652***	-3.125***	-3.321***	-1.776***	-1.732***	-2.241***	-2.726***	-2.947***
						(0.167)	(0.129)	(0.124)	(0.135)	(0.172)	(0.166)	(0.127)	(0.121)	(0.133)	(0.170)
Urban area											3.594***	2.669***	0.449	-2.145***	-4.245***
											(0.443)	(0.325)	(0.284)	(0.284)	(0.342)
Female math teacher											1.912***	1.306***	1.488***	1.236***	1.265***
											(0.238)	(0.189)	(0.187)	(0.207)	(0.264)
Positive belief											3.157***	4.143***	5.102***	5.766***	6.208***
											(0.198)	(0.152)	(0.144)	(0.153)	(0.190)
Aggression											-1.425***	-1.477***	-2.033***	-2.285***	-2.908***
											(0.227)	(0.176)	(0.169)	(0.183)	(0.231)
White weapon											-1.308***	-1.615***	-2.035***	-1.764***	-1.563***
											(0.480)	(0.366)	(0.338)	(0.349)	(0.414)
Socioeconomic status											5.669***	6.495***	8.029***	8.821***	9.844***
											(0.176)	(0.136)	(0.132)	(0.149)	(0.199)
Federal school											1.489	3.609***	9.544***	26.28***	54.93***
											(1.031)	(0.949)	(1.241)	(2.045)	(4.339)
State school											-4.446***	-8.744***	-19.01***	-35.10***	-56.22***
											(0.585)	(0.524)	(0.626)	(0.933)	(1.652)
Municipal school											-1.162**	-5.209***	-14.94***	-30.31***	-50.81***
											(0.587)	(0.528)	(0.631)	(0.939)	(1.659)
Constant	286.4***	306.0***	330.9***	351.8***	366.6***	267.3***	285.1***	306.6***	326.3***	339.1***	244.8***	261.9***	285.3***	315.9***	344.9***
	(2.177)	(1.469)	(1.223)	(1.187)	(1.398)	(2.397)	(1.642)	(1.399)	(1.395)	(1.680)	(2.824)	(2.026)	(1.868)	(2.061)	(2.818)

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses.

Table 8 – Unconditional quantile regression extended results – 3rd grade (high school).

Variables	(2) 10%	(2) 25%	(2) 50%	(2) 75%	(2) 90%	(3) 10%	(3) 25%	(3) 50%	(3) 75%	(3) 90%	(4) 10%	(4) 25%	(4) 50%	(4) 75%	(4) 90%
Female	-2.577***	-5.347***	-7.321***	-8.130***	-9.742***	-2.236***	-4.767***	-6.587***	-7.415***	-9.036***	-1.929***	-4.356***	-6.142***	-7.046***	-8.710***
	(0.193)	(0.174)	(0.168)	(0.172)	(0.222)	(0.192)	(0.172)	(0.165)	(0.170)	(0.221)	(0.189)	(0.168)	(0.161)	(0.167)	(0.219)
Black	-15.66***	-18.95***	-19.00***	-15.57***	-13.46***	-13.51***	-16.29***	-16.32***	-13.30***	-11.42***	-12.49***	-14.74***	-14.37***	-11.41***	-9.547***
	(0.398)	(0.324)	(0.264)	(0.225)	(0.253)	(0.395)	(0.321)	(0.262)	(0.224)	(0.253)	(0.391)	(0.315)	(0.259)	(0.224)	(0.254)
Age	-6.109***	-6.252***	-5.148***	-3.411***	-2.616***	-4.762***	-4.645***	-3.551***	-2.066***	-1.394***	-3.683***	-3.171***	-1.913***	-0.649***	-0.0896
	(0.168)	(0.125)	(0.0968)	(0.0854)	(0.102)	(0.168)	(0.124)	(0.0965)	(0.0856)	(0.103)	(0.166)	(0.121)	(0.0947)	(0.0849)	(0.103)
Flunked school	-15.85***	-19.98***	-19.62***	-15.16***	-12.49***	-13.88***	-17.69***	-17.43***	-13.33***	-10.84***	-12.97***	-16.25***	-15.68***	-11.67***	-9.275***
	(0.262)	(0.201)	(0.148)	(0.117)	(0.128)	(0.260)	(0.200)	(0.148)	(0.118)	(0.128)	(0.258)	(0.196)	(0.147)	(0.118)	(0.128)
Pre-school	2.277***	4.327***	5.916***	5.930***	5.816***	2.879***	4.993***	6.555***	6.486***	6.360***	1.978***	3.504***	4.887***	5.149***	5.331***
	(0.201)	(0.184)	(0.182)	(0.190)	(0.247)	(0.200)	(0.182)	(0.179)	(0.188)	(0.246)	(0.203)	(0.183)	(0.179)	(0.188)	(0.247)
Math homework	17.16***	21.86***	21.88***	17.63***	14.64***	12.84***	16.86***	17.25***	13.96***	11.48***	10.07***	12.68***	12.56***	9.868***	7.770***
	(0.517)	(0.411)	(0.312)	(0.240)	(0.249)	(0.518)	(0.411)	(0.313)	(0.243)	(0.254)	(0.530)	(0.416)	(0.320)	(0.254)	(0.271)
Housework	-1.469***	-1.953***	-1.967***	-1.604***	-1.371***	-1.357***	-1.790***	-1.786***	-1.447***	-1.223***	-1.073***	-1.237***	-1.049***	-0.680***	-0.433***
	(0.0866)	(0.0763)	(0.0698)	(0.0672)	(0.0827)	(0.0859)	(0.0752)	(0.0687)	(0.0665)	(0.0822)	(0.0889)	(0.0763)	(0.0689)	(0.0669)	(0.0830)
Labor	-27.98***	-29.00***	-23.08***	-16.59***	-13.87***	-26.96***	-28.04***	-22.32***	-16.03***	-13.32***	-23.90***	-24.42***	-18.73***	-13.13***	-10.72***
	(0.432)	(0.331)	(0.257)	(0.219)	(0.252)	(0.428)	(0.326)	(0.254)	(0.219)	(0.254)	(0.421)	(0.318)	(0.249)	(0.217)	(0.253)
Mom's schooling						1.190***	1.327***	1.256***	1.086***	1.059***	0.974***	1.075***	0.989***	0.834***	0.807***
						(0.0213)	(0.0189)	(0.0173)	(0.0168)	(0.0209)	(0.0214)	(0.0188)	(0.0172)	(0.0168)	(0.0209)
Family size						-1.367***	-2.257***	-2.898***	-2.399***	-2.064***	-0.475***	-1.191***	-1.886***	-1.651***	-1.456***
						(0.0884)	(0.0753)	(0.0684)	(0.0662)	(0.0814)	(0.0878)	(0.0738)	(0.0672)	(0.0655)	(0.0812)
Socioeconomic status						0.928***	1.364***	1.513***	1.341***	1.181***	0.0956***	0.348***	0.507***	0.562***	0.521***
						(0.0251)	(0.0215)	(0.0201)	(0.0204)	(0.0262)	(0.0261)	(0.0219)	(0.0206)	(0.0211)	(0.0272)
Incentive						4.731***	5.032***	4.107***	2.943***	2.453***	4.109***	4.142***	3.094***	2.047***	1.613***
						(0.163)	(0.131)	(0.109)	(0.101)	(0.124)	(0.162)	(0.128)	(0.107)	(0.0996)	(0.123)
Reading habits						0.995***	0.183	-0.459***	-0.848***	-1.331***	0.993***	0.371**	-0.0709	-0.375***	-0.774***
						(0.184)	(0.157)	(0.143)	(0.141)	(0.179)	(0.182)	(0.153)	(0.140)	(0.139)	(0.179)
Urban area											7.097***	4.139***	-0.424	-3.211***	-5.218***
											(0.450)	(0.354)	(0.292)	(0.267)	(0.326)
Female math teacher											0.116	1.222***	1.109**	0.999**	1.979***
											(0.522)	(0.468)	(0.452)	(0.470)	(0.636)
Positive belief											2.819***	3.887***	4.373***	3.988***	3.812***
											(0.166)	(0.143)	(0.129)	(0.125)	(0.154)
Aggression											-1.507***	-2.084***	-2.919***	-3.436***	-4.043***
											(0.198)	(0.176)	(0.168)	(0.171)	(0.218)
White weapon											-2.044***	-2.842***	-3.201***	-2.483***	-2.666***
											(0.606)	(0.519)	(0.456)	(0.421)	(0.492)
Socioeconomic status											5.729***	7.061***	8.228***	8.476***	9.103***
											(0.151)	(0.133)	(0.131)	(0.139)	(0.188)
Federal school											-1.581	-0.449	6.587**	4.825	7.252
											(1.558)	(1.989)	(2.563)	(3.703)	(5.987)
State school											-0.0310	-5.987***	-13.40***	-16.75***	-18.59***
											(0.630)	(0.702)	(0.890)	(1.238)	(1.970)
Municipal school											0.113	-6.008***	-14.03***	-18.49***	-20.66***
											(0.618)	(0.692)	(0.882)	(1.230)	(1.959)
Constant	230.3***	258.0***	280.3***	295.8***	317.3***	174.9***	198.8***	229.5***	255.7***	282.7***	155.3***	180.6***	213.4***	236.8***	260.8***
	(1.865)	(1.398)	(1.092)	(0.962)	(1.147)	(2.108)	(1.597)	(1.275)	(1.143)	(1.380)	(2.370)	(1.931)	(1.777)	(1.917)	(2.670)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

2.B Appendix – Oaxaca-Blinder decomposition results

Table 9 – Oaxaca-Blinder decomposition summarized results – all grades.

	Fifth grade					Ninth grade					Third grade (high school)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Composition effect	4.350	5.392	-4.877	-3.101	-1.930	-4.489	-3.816	-3.323	-2.314	-1.261	-1.334	-0.729	0.503	3.073	6.102
Individual characteristics	3.757	4.832	-4.418	-2.834	-1.750	-5.362	-4.961	-4.850	-4.015	-2.984	-1.898	-1.803	-1.452	-1.376	-0.127
Family background	0.432	0.356	-0.226	-0.061	-0.009	0.570	0.807	1.136	1.303	1.327	0.217	0.584	1.140	2.444	3.458
School characteristics	0.160	0.204	-0.233	-0.206	-0.171	0.302	0.339	0.391	0.398	0.396	0.346	0.490	0.816	2.006	2.771
Return effect	-1.026	-3.988	6.171	6.898	8.031	7.522	11.509	16.731	16.790	14.258	2.883	7.720	15.565	16.616	13.490
Individual characteristics	-2.283	11.774	-17.224	-13.764	-10.723	15.465	-2.236	-14.687	-5.015	0.922	-6.168	-37.016	-41.074	17.164	-5.711
Family background	-0.673	-5.281	1.585	-1.289	-1.880	-8.262	-11.197	-18.291	-20.419	-20.652	-9.862	-9.726	-13.296	-17.586	-28.935
School characteristics	-6.548	-4.890	0.307	-0.488	2.248	14.194	14.164	14.100	9.833	4.098	6.213	7.323	9.053	13.399	12.998
Constant	8.478	-5.591	21.504	22.439	18.386	-13.875	10.778	35.609	32.392	29.891	12.700	47.139	60.881	3.639	35.138

Note: The sum of individual, family and school characteristics (and constant, in the case of return effects) equals total effects.

Table 10 – Oaxaca-Blinder decomposition extended results – all grades.

	Fifth grade					Ninth grade					Third grade (high school)				
	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%	10%	25%	50%	75%	90%
Composition effect															
Individual characteristics															
Black	0.280	0.372	-0.336	-0.254	-0.186	-0.184	-0.180	-0.211	-0.222	-0.235	-0.061	-0.065	-0.091	-0.146	-0.177
Age	0.637	0.710	-0.220	0.008	0.109	-1.548	-1.043	-0.685	-0.421	-0.249	-0.813	-0.763	-0.631	-0.504	0.076
Flunked school	1.280	1.783	-2.146	-1.437	-0.930	-1.880	-2.124	-2.407	-2.287	-1.998	-0.684	-0.831	-1.028	-1.471	-1.278
Pre-school	0.017	0.036	-0.056	-0.058	-0.051	-0.185	-0.189	-0.224	-0.237	-0.229	-0.024	-0.027	-0.027	-0.028	0.026
Math homework	0.162	0.221	-0.209	-0.158	-0.100	-0.258	-0.233	-0.237	-0.244	-0.248	-0.087	-0.094	-0.104	-0.162	-0.215
Housework	-0.263	-0.290	0.150	0.085	0.056	-0.987	-1.013	-0.979	-0.525	0.078	-0.145	-0.040	0.445	1.568	2.607
Labor	1.645	1.999	-1.600	-1.021	-0.648	-0.320	-0.179	-0.106	-0.078	-0.104	-0.084	0.016	-0.016	-0.633	-1.165
Family background															
Mom's schooling	-0.047	-0.056	0.044	0.039	0.033	0.464	0.511	0.633	0.698	0.706	0.360	0.532	0.770	1.291	1.181
Family size	-0.001	-0.004	0.011	0.010	0.008	0.020	0.039	0.056	0.046	0.039	-0.016	-0.004	0.006	0.014	0.009
Socioeconomic status	-0.022	-0.091	0.117	0.145	0.126	0.152	0.284	0.474	0.619	0.677	-0.161	0.019	0.290	1.106	2.366
Incentive	0.451	0.505	-0.396	-0.272	-0.211	-0.023	0.010	0.022	0.006	-0.015	0.052	0.062	0.101	0.076	-0.061
Reading habits	0.051	0.002	-0.002	0.016	0.036	-0.042	-0.037	-0.049	-0.067	-0.079	-0.017	-0.026	-0.028	-0.043	-0.037
School characteristics															
Urban area	0.023	0.015	0.003	0.009	0.011	0.008	0.005	-0.003	-0.012	-0.018	-0.005	-0.010	-0.011	-0.015	-0.013
Female math teacher	0.001	0.001	-0.002	-0.002	-0.002	0.004	0.003	0.003	0.003	0.003	-0.005	-0.008	-0.011	-0.005	0.007
Positive belief	0.050	0.069	-0.080	-0.070	-0.055	-0.029	-0.037	-0.046	-0.057	-0.066	0.046	0.050	0.069	0.097	0.080
Aggression	0.010	0.010	-0.017	-0.021	-0.022	-0.003	-0.003	-0.004	-0.005	-0.007	-0.001	-0.001	-0.005	-0.015	-0.020
White weapon	0.002	0.003	-0.004	-0.004	-0.002	0.000	0.000	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	-0.001
Socioeconomic status	-0.007	-0.010	0.009	0.010	0.009	0.181	0.192	0.233	0.263	0.315	0.070	0.149	0.365	1.217	2.519
Federal school	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.003	0.006	0.033	0.051	0.082	0.228	0.280
State school	0.006	-0.021	0.048	0.058	0.050	-0.049	-0.089	-0.189	-0.362	-0.583	0.214	0.316	0.496	1.110	1.222
Municipal school	-0.006	0.021	-0.052	-0.065	-0.060	0.024	0.065	0.171	0.357	0.587	0.002	0.002	0.001	0.003	0.013
Return effect															
Individual characteristics															
Black	-0.126	0.096	-0.200	-0.252	-0.332	-0.276	-0.267	-0.412	-0.262	-0.081	-0.470	-0.805	-0.915	-0.258	-0.213
Age	-2.613	11.908	-18.092	-14.265	-12.180	10.958	-5.141	-17.208	-5.433	0.949	-10.539	-40.245	-43.739	15.368	-7.054
Flunked school	-1.220	-0.889	0.563	-0.252	-0.899	2.071	1.924	1.110	0.858	0.505	0.448	0.014	-0.348	1.646	0.548
Pre-school	0.227	0.134	0.001	0.106	0.378	0.614	0.889	1.249	1.062	0.977	0.286	0.862	0.590	-0.452	1.116
Math homework	0.634	-0.622	1.303	1.601	3.053	5.262	2.868	2.194	-1.156	-2.517	4.931	4.265	4.714	-2.118	-4.660
Housework	1.557	1.390	-0.600	-0.342	-0.081	-2.178	-1.485	-0.515	0.798	1.821	0.735	0.759	0.391	3.140	4.328
Labor	-0.742	-0.242	-0.200	-0.361	-0.661	-0.984	-1.023	-1.105	-0.882	-0.732	-1.557	-1.866	-1.767	-0.160	0.224
Family background															
Mom's schooling	-1.350	-2.378	1.132	0.074	1.583	-1.535	-1.278	-1.057	-2.725	-3.154	-2.287	-0.148	1.975	-7.784	-5.941
Family size	-2.799	-3.408	1.632	1.340	-0.798	1.471	0.963	0.674	1.793	2.697	-1.705	1.534	1.904	4.277	3.173
Socioeconomic status	0.207	-0.524	1.297	-0.055	0.251	-2.696	-2.146	-2.678	-4.132	-6.021	-0.196	-1.792	-2.033	-6.884	-16.100
Incentive	2.987	-0.048	-1.597	-1.655	-2.202	-4.164	-7.238	-14.012	-15.313	-15.054	-7.110	-8.897	-12.688	-8.488	-14.126
Reading habits	0.281	1.077	-0.879	-0.992	-0.714	-1.338	-1.498	-1.218	-0.042	0.880	1.436	-0.422	-2.453	1.293	4.059
School characteristics															
Urban area	-3.713	-3.069	1.689	0.961	-1.252	3.518	3.082	2.763	2.100	1.268	7.710	6.103	4.453	1.447	2.389
Female math teacher	-0.010	0.018	-0.036	-0.078	-0.050	0.168	0.107	0.075	-0.037	-0.073	0.439	0.039	-0.053	-0.094	0.203
Positive belief	0.053	-0.162	-0.213	0.447	2.107	1.537	1.665	1.968	0.630	-0.396	3.211	4.034	4.817	-2.221	-1.390
Aggression	0.267	-0.065	0.086	0.261	0.033	-0.328	-0.320	-0.295	-0.054	-0.044	-0.538	-1.097	-0.635	0.189	0.147
White weapon	0.014	-0.001	0.016	0.038	-0.040	-0.061	-0.048	-0.036	-0.014	0.078	0.131	0.056	0.063	0.103	0.303
Socioeconomic status	-2.468	-5.627	4.331	2.573	9.685	3.936	4.967	8.071	5.052	0.524	3.237	4.438	13.002	-4.344	-13.240
Federal school	0.004	0.003	0.002	0.009	0.004	0.003	0.003	0.008	0.018	0.023	0.086	0.101	0.251	-0.193	-0.076
State school	-0.488	-0.002	-0.443	-0.946	-2.130	0.818	0.894	0.394	1.485	2.638	-2.478	-4.061	-8.031	15.041	25.114
Municipal school	-1.565	-0.347	-1.789	-3.924	-8.192	1.177	1.165	0.907	1.672	2.044	0.016	0.010	-0.009	0.019	0.093
Constant	8.478	-5.591	21.504	22.439	18.386	-13.875	10.778	35.609	32.392	29.891	12.700	47.139	60.881	3.639	35.138

Note: State coefficients omitted.

3 GENDER STEREOTYPE IN STEM IN A BRAZILIAN UNIVERSITY

3.1 Initial remarks

In this day and age, women represent most of the students in tertiary education (colleges and university) around the world (United Nations Educational, Scientific and Cultural Organization (UNESCO), 2020). This fact is illustrative of Brazil – in 2017, over 4,7 million Brazilian women enrolled in university to pursue an undergraduate degree, corresponding to 57% of total enrollments (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, 2019). Among the 20 most popular majors, women constitute the majority of students in no less than 14 of them, featuring Pedagogy (92,5%), Social Services (90,1%), Nutrition (85,2%), Nursing (84,0%) and Psychology (80,5%)[1]. On the other hand, men prevail in majors such as Mechanical Engineering (89,7%), Civil Engineering (69,5%), Production Engineering (65,0%) and Entrepreneurship (52,4%). (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, 2019). So why is it that Brazilian women are so over-represented in humanities and care majors, and so underrepresented in engineering?

Choices of higher education tend to reflect expectations about the returns to additional education, as well as innate ability and earlier educational attainment (ALTONJI; BLOM; MEGHIR, 2012). For example, there exists evidence connecting the gender gap in mathematical achievement with gender differences in choice of majors and, consequently, with the gender gap in future income (BHARADWAJ et al., 2016). Additionally, Levine and Zimmerman (1995) demonstrate that additional math and science courses taken by women during secondary school are associated with the choice of technical majors and therefore with an increase of the proportion of women in math-related jobs[2].

Another interesting fact to consider is that Brazilian women work, on average, 7,5 more hours than Brazilian men on a weekly basis, accounting for both paid and unpaid labor (FONTOURA et al., 2016). Moreover, between 1995 and 2015 the

[1] Other courses in which women predominate are Odontology (72,2%), Farmacy (71,9%), Physiotherapy (79,0%), Human Resources (78,0%), Architecture (66,6%), Medicine (58,2%), Accounting (57,0%), Law (55,3%) and Business (54,9%) (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, 2019). See Nosek, Banaji and Greenwald (2002) and Beede et al. (2011) for similar distributions of gender across majors, in the United States.

[2] This happens because those additional math and science courses increase educational attainment as a whole (LEVINE; ZIMMERMAN, 1995). This is substantiated by Rose and Betts (2004) who have found that an additional year of math raises wages significantly even after controlling for math test scores

proportion of women in the labor market in the country has stagnated around 55%, despite the rise in average years of education, relative to men (FONTOURA et al., 2016). This seems to reflect both the fact that the ratio of female to male students in math-related areas diminishes as the level of education increases (NOSEK; BANAJI; GREENWALD, 2002), and the persistence of domestic and care work as female occupations (ENGLAND; FOLBRE, 1999). About the latter, it appears to operates both through the unpaid domestic work structure (PERRONS, 2000) that also may keep women from performing paid labor, and through the specialization of women as paid care professionals. In Brazil this is substantiated by the aforementioned representation of women in care-related majors, by the fact that the gender composition of occupations has remained mostly unchanged over the last decades (FONTOURA et al., 2016) and, finally, by the fact that the bulk of unpaid work in Brazil is still performed by women – over 90% of women perform unpaid household chores, while the proportion of men is 53% (FONTOURA et al., 2016).

Therefore, the fact that care work is associated with women (ENGLAND; FOLBRE, 1999) while math-related jobs are traditionally connected to men, seem to be related to the tradition of gender inequality in Brazil, one of the most gender-unequal countries in Latin America, ranking in the ninety-second position of the Gender Gap Index (GGI) (World Economic Forum, 2019)[3]. With the understanding that observed gender differences in math-intensive fields have lasting effects on gender inequality in the labor market; and that observed gender differences do not necessarily associate with differences in innate ability, but often with prescribed gender roles (SENT; STAVEREN, 2019), in this study we explore the relation between one of the main aspects of societal gender bias – gender stereotypes – and gender differences in fields of major in a Brazilian university.

In this interest, we conduct a social experiment at Universidade Federal de Viçosa (UFV) in Southeastern Brazil, by adapting and applying an instrument that is able to capture the implicit gender stereotype at an individual level – the gender-STEM Implicit Association Test (IAT). The IAT, created by Greenwald, McGhee and Schwartz (1998) is commonly used within social-psychological experiments, from which it has been demonstrated that men are more implicitly associated with math and science while women are associated more with arts and humanities (NOSEK; BANAJI; GREENWALD, 2002). In a similar approach to the one of this research, Smeding (2012), found that "female engineering students held weaker implicit gender-math and gender-reasoning stereotypes than female humanities".

Gender stereotypes are defined as beliefs that men and women are differentiated by a set of attributes (ASHMORE; BOCA, 1981) and they can be thought as stemming

[3] Position 92 among 153 countries (World Economic Forum, 2019)

from social roles, that is, "the tendency of perceivers to observe women in lower status roles than men" (EAGLY; STEFFEN, 1984). Related, implicit stereotypes are automatic associations that people make between a group (for example, *men*) and an attribute or domain (like *math*). It differs from an *explicit* stereotype in that it is unconscious and involuntary (GREENWALD; BANAJI, 1995).

Our main objective is to assess if implicitly gender-STEM stereotypes correlate negatively with the (already given) choice of math-intensive majors by women at UFV. This will contribute in assessing how "gender culture" ((HINTON, 2017)) may be shaping Brazilian women's major choices and in deriving a policy-relevant path to counter gender inequality in the country. We depart from the approach of Smeding (2012) by designing the so-called gender-STEM IAT to fit the idiosyncrasies of tertiary education in Brazil, as well as by analysing the results using a discrete, qualitative method.

3.2 Theoretical framework

In the words of Lave (1988), "cognition observed in everyday practice is distributed – stretched over, not divided among – mind, body, activity and culturally organized settings (which include other actors)". The introspective process that occurs within conscious experience does not correspond to what actually goes on inside one's mind (NOSEK; HAWKINS; FRAZIER, 2011). For that reason, it is common that explicit reports of one's social perception do not accurately describe such perception, even when the individual is fully motivated to answer honestly and in a state of conscious awareness.

In social psychology, the scientific field concerned with the nature of individual behavior in social contexts[4], implicit measures of social psychological constructs (defined below) have been extensively used in the field due to its "practical value for predicting human behavior" (NOSEK; HAWKINS; FRAZIER, 2011). The term *implicit social cognition* was coined by Greenwald and Banaji (1995) to characterize cognitive operations – within social psychological constructs – that take place outside the realm of consciousness. The constructs of social psychology which are of central importance to this research are attitudes, stereotypes, self-esteem and self-concepts.

Attitude is a tendency expressed by the evaluation of an agent or event (EAGLY; CHAIKEN, 1993). It refers to what a person views positively or negatively, her likes and dislikes (PETTY; BRINOL, 2011). It does not consist of an immutable concept – contextual or permanent changes in attitude may occur, for example, when a person is exposed to new experiences, forming new memories and updating judgements. Formally,

[4] Myers and Twenge (2013) defines social psychology as "a science that studies the influences of our situations, with special attention to how we view and affect one another". More precisely, it is the scientific study of how people think about, influence, and relate to one another.

the shape of an *attitude* is a combination of *affect*, *beliefs* and *behaviors* (ALBARRACIN; JOHNSON; ZANNA, 2014). *Affect* relates to feelings a person experiences, which are not necessarily related to an agent or event; while *beliefs* are perceptions about the probability that an attribute is related with an agent or event. It is, therefore, a cognitive response to an entity. Finally, *behaviors* are the explicit actions of an individual (ALBARRACIN; JOHNSON; ZANNA, 2014). In the empirical literature, attitudes are said to be predictive of behavior both when they are *conscious* during the process leading to action (EAGLY; CHAIKEN, 1993) or *unconscious* (GREENWALD; BANAJI, 1995), with the latter being more frequent up until the rise of implicit social cognition.

The definition of *stereotype* differs from *attitude* in that a stereotype is a *non-evaluative* association of an social group with one or more characteristics, *i.e.*, it does not involve a defined positive or negative association. Accordingly, "whereas an attitude implies a consistent evaluative response to its object, a stereotype may encompass [social] beliefs with widely diverging evaluative implications" (GREENWALD; BANAJI, 1995). According to Katz and Braly (1935), "a stereotype is a fixed impression, which conforms very little to the fact it pretends to represent, and results from our defining first and observing second". The implicit nature of action predicted by stereotype is more widespread in the literature of experimental social psychology, in relation to other constructs. For example, it has been demonstrated that race stereotyping has a much stronger presence and a more pronounced effect on behavior than explicit data would lead one to believe (CROSBY; BROMLEY; SAXE, 1980; GREENWALD; BANAJI, 1995).

Self-esteem is a class of attitude (GREENWALD; BANAJI, 1995): it associates not a *social group*, but the *self* with a evaluative attribute, *i.e.*, self-esteem consists of an attitude towards self. *Self-concept* also associates the *self* with an attribute, but one which does not directly entail a positive/negative connotation. It relates the concept of self to trait attributes, roles, groups, objects, activities and so on (SCHNABEL; ASENDORPF, 2011). Hence the possibility of mediation of the self-esteem through the self-concept: one can relate the self with a trait like "outgoing" and associate such a trait with positive valence, for example. Schnabel and Asendorpf (2011) states that "self-esteem rather represents the affective part of the self-concept than an entity independent from the self-concept".

3.2.1 The theory of balance

The theory of balance was formalized by Heider (1946). The key hypothesis behind this framework is that interconnections among concepts like attitudes, stereotypes and self-concepts organize themselves in such a way that a cognitive balance is achieved, i.e., these concepts become mutually consistent (CVENCEK; MELTZOFF;

GREENWALD, 2011). In the words of Heider (1946): "Attitudes towards persons and causal unit formations influence each other. An attitude towards an event can alter the attitude towards the person who caused the event, and, if the attitudes towards a person and an event are similar, the event is easily ascribed to the person. A balanced configuration exists if the attitudes towards the parts of a causal unit are similar". For example, the stereotype "Math is for boys" combined with the gender-identity (self-concept) "I am a girl" balance each other and influence the self-concept "Math is not for me" (CVENCEK; MELTZOFF; GREENWALD, 2011).

The theoretical constructs of such relations are described by Heider (1946) as follows. A positive attitude L of a person p to another person o or to an entity[5] x is represented by pLo and pLx, respectively; a negative attitude towards another person is written as $p \sim Lo$ and as $p \sim Lx$ to describe a negative attitude towards an entity. Examples of attitudes are *to like* and *to esteem* and their opposites. The representation of the relation unity U is similar to that of L. Examples are *similarity*, *membership* and *possession*. Therefore, pUx can mean that p owns x and $p \sim Uo$ can mean that person p does not identify with person o.

Formally, in Heider (1946) the hypothesis sustaining the balance theory can be stated as:

- If pLo is true for all meanings of L, then a balanced state exists. The same holds for $p \sim Lo$, pLx and $p \sim Lx$.
- If pUo is true for all parts of U, and if entities with $p \sim Uo$ are segregated from each other, then a balanced state exists. The same holds for other combinations of p with o and x.
- If no balanced state exists, then forces towards a balanced state will arise.

"By a balanced state is meant a situation in which the relations among the entities fit together harmoniously; there is no stress towards change" (HEIDER, 1958). Therefore, there exists a tendency to make different dynamic relations agree with each other through what Heider (1946) called "cognitive restructuring". More intuitively, people make use of rationalizations or excuses to restructure concept relations in a way that such relations become harmonious. Take the case pLo: *p loves o* does not necessarily imply *p admires o*, and vice-versa, but there exists a tendency to admire a loved person and to love an admired person (HEIDER, 1946).

[5] An entity in this setting could be an object, an event, an idea, and so on (HEIDER, 1946)

3.2.2 The theory of implicit social cognition

The unified theory of implicit social cognition (GREENWALD et al., 2002) shares principles with the theory of balance (HEIDER, 1946). Greenwald et al. (2002) relied on Heider (1946) theoretical constructs, although the motivation for constructing a unified theory came from empirical research. The theory integrates important cognitive and affective constructs of social psychology, and the theoretical definitions of such constructs stem from the association among concepts[6]. In the case of cognitive constructs, namely stereotype and self-concept, societal and self concepts are associated with one or more non-valence attributes, that is, with characterizations of a social group (stereotype) or individual (self-concept) that do not involve valences like positive/negative or good/bad. On the other hand, affective constructs, namely attitude and self-esteem, are associations of social group/object and self concepts with valence attribute concepts. For example, a person that associates *self* with *positive* is likely to have a high self-esteem. In the same spirit, the association of the attribute trait *intelligent* with the *positive* valence characterizes an attitude. Let "—" represent an association. Following Greenwald et al. (2002), the theoretical definitions of the referred social psychology's constructs can be represented as:

- *Attitude*: concept of social object or social group — concept of valence attribute
- *Stereotype*: concept of social group — concept of non-valence attribute(s)
- *Self-esteem*: concept of self — concept of valence attribute
- *Self-concept*: concept of self — concept of non-valence attribute(s)

Figure 6 is a diagrammatic representation of a social knowledge structure (SKS) in the psyche of an elderly female academic from Greenwald et al. (2002). Nodes represent concepts and lines represent associations. The thickness of the lines represent strength of association. Note that the self-concept is represented by links of the *me* node to non-valence attributes such as *professor, intelligent, athletic, nurturing* and self-esteem consists of the direct link of the *me* node to the *positive* valence attribute, as well as the indirect associations of the *me* node to valence attribute concepts through components of the self-concept, e.g., *me—professor—positive*. Stereotypes are all links of group concepts like old person and male with attribute concepts, e.g. *male—strong*. Finally, attitude is the combination of links of social group concepts to valence concepts,

[6] One of the central assumptions of the theory (and of social psychology theory in general) is that "an important portion of social knowledge can be represented as a network of variable-strength associations among person concepts (including self and groups) and attributes (including valence)" (GREENWALD et al., 2002). They also assume *self's centrality* and *self-positivity*. For more on the theoretical assumptions see Greenwald et al. (2002)

which may or may not be mediated by components of stereotype, like the associations *professor—positive* and *female—grandmother—positive*.

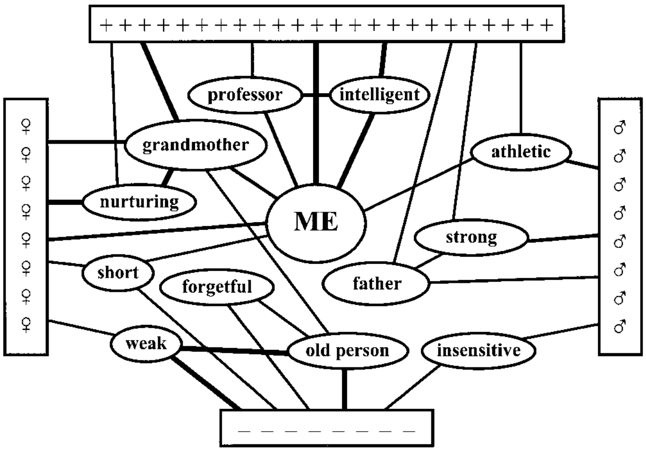


Figure 6 – The social knowledge structure of an elderly female academic.
Source: Greenwald et al. (2002)

Three principles of the theory of Greenwald et al. (2002) govern the associative strengths of relations among the described constructs of the SKS. They are defined as follows:

Principle 1 ***Balance-congruity***. *When two unlinked or weakly linked nodes share a first-order link, i.e., when they are both linked to the same third node, the association between these two links should strengthen.*

Principle 2 ***Imbalance-dissonance***. *The network resists the formation of new links that would result in a node having first-order links to both of two bipolar-opposed nodes, i.e., nodes which have fewer shared first-order links than expected by chance.*

Principle 3 ***Differentiation***. *Pressured concepts, i.e., concepts which develop links to both of two bipolar-opposed nodes, tend to split into sub-concepts, each linked to a different one of the pressuring bipolar opposed nodes.*

Looking at Figure 6, Principle 1 has the tendency to reinforce links like *me—male*, given that both concepts are linked to *athletic*, that is, they share a first-order link. Principle 2 avoids the production of links among all pairs of nodes that otherwise would occur by Principle 1. Using the same example as before, Principle 2 resists the formation of the link *me—male*, given that there already exists the association *me—female* and *male* and *female* are bipolar-opposed nodes. Finally, Principle 3 eliminates pressures toward change driven by Principle 1 and that are prevented by Principle 2, avoiding imbalanced configurations (GREENWALD et al., 2002).

3.3 Experimental design: The Implicit Association Test

The Implicit Association Test (IAT) is a widely researched method in experimental social psychology, often defined as a "response competition task" (NOSEK; BANAJI; GREENWALD, 2002) or an "individual difference measure" (FAZIO, 2001). The test – in its various forms[7] – has been applied to over a million people around the world and is available at Project Implicit, a non-profit organization with the goal to "educate the public about hidden biases and to provide a *virtual laboratory* for collecting data on the Internet" (Project Implicit, 2011). The framework of the test implementation is available as a *open code* in the internet, and it was the basis to the experiment developed in this study.

Thus, in the context of this research, the IAT will allow us to observe whether female undergraduates in Universidade Federal de Viçosa (UFV) who attend STEM courses display a weaker gender-STEM stereotype, relative to arts and humanities female undergraduates. The evidence will enable the partial verification of the hypothesis of this research, supported by the underlying theory described previously – stereotypical beliefs influence individual self-concepts in such a way that women dis-identify with math and, therefore, with STEM majors.

3.3.1 Self-report measure

Before administering the IAT itself (details in the next section) the respondents answer a questionnaire requesting basic socio-demographic information, as well as questions that allow us to obtain an explicit measure that will be compared with the implicit measure from the IAT results. For that purpose, we apply a thermometer-type score. Respondents are asked to associate the concepts *exact and natural sciences* and *human sciences* with a score varying from 1 to 5, meaning respectively: strongly male, somewhat male, neither male or female, somewhat female, strongly female. The thermometer measure is the difference between the math and the language score. Adapting from Greenwald, Nosek and Banaji (2003), the thermometer items are as follows:

> Please rate how much you associate the following domains with males or females.
>
> - Exact and Natural Sciences
> - Human Sciences

[7] Examples of IAT tests available at Project Implicit (2011) are Age IAT, Race IAT, Sexuality IAT, Religion IAT and others.

3.3.2 The Implicit Association Test (IAT)

The IAT does not rely on introspective experience, but on the existence of "well-established associations" within one's mental operations (GREENWALD; MCGHEE; SCHWARTZ, 1998). It consists of a *thought* experiment in which an individual's implicit attitude is measured by the strength of association between concepts and attributes (GREENWALD; MCGHEE; SCHWARTZ, 1998). For this study, the concepts are *male* and *female* and the attributes are *exact and natural sciences* and *human sciences*; and the main measure of implicit attitude is the *implicit gender-STEM stereotype*[8]. This is measured, roughly, by the differential time it takes for a person to complete *stereotype congruent* and *stereotype incongruent* computer assignments.

Stereotype congruent assignments in the IAT design are those in which *male names* share a computer key with *exact and natural sciences words*, while *female names* share a computer key with *human sciences words*. Stereotype incongruent tasks pair *male names* with *human sciences words* and *female names* with *exact and natural sciences words* (CVENCEK; MELTZOFF; GREENWALD, 2011). The principle is that people with stronger implicit gender-STEM stereotype should take longer to respond to stereotype incongruent tasks than to stereotype congruent ones[9].

The predictive power of the IAT in the assessment of stereotypes and attitudes relies on the fact that one concept is assessed relatively to the other, as in the pair *Exact and Natural Sciences* and *Human Sciences*. In line with our theoretical framework, we state that stronger implicit STEM-male stereotypes implies more negative math and science attitudes for women, which are reflected in some women's difficulty in associating themselves with math[10] (NOSEK; BANAJI; GREENWALD, 2002).

3.3.3 Subjects

In order to comply with the objectives of our study, Greenwald, Nosek and Banaji (2003) suggest a sample of at least 39 subjects. Although such a sample would not grant any external validity, it should be enough to yield consistent results, internally. We need there to be a balanced composition of male and female subjects from both STEM and humanities courses. A strategy used by Nosek, Banaji and Greenwald (2002) in their experiment was to give the IAT to their students in fulfilment of course credit. In the

[8] In the context of this research, we use the terms *exact and natural sciences* and *STEM* interchangeably, considering that in Brazil the former usage is more widely spread, and because of that it was the term employed in the experiment, with the proper Portuguese translation. On the other hand, the term STEM is widely used in the literature, and it is conceptually adequate for the purposes of this research.

[9] See (CVENCEK; MELTZOFF; GREENWALD, 2011) for a complete description of such mechanisms in the context of the math-gender IAT.

[10] We also rely on strength of gender identity for such implication.

present study, we make use of the institutional e-mail to send alerts to all students enrolled in the university, inviting them to take the test. This task is simplified by the fact the the gender-STEM IAT is hosted on a server and is available online by clicking in the link informed in said e-mail.

3.3.4 Procedure

Adapting from Nosek, Banaji and Greenwald (2002) and Nosek, Greenwald and Banaji (2005), the IAT procedure has 7 blocks:

1. *Learning the concept dimension:* Respondents sort stimuli words from **exact and natural sciences** and **human sciences** concepts into their superordinate categories. They use the left key of the computer keyboard for **exact and natural sciences** concepts and the right key for **human sciences** concepts.

2. *Learning the attribute dimension:* Respondents sort stimuli words representing male and female trait attributes into their superordinate categories. They use the left key for male attributes and the right key for female attributes.

3. *Concept-attribute pairing (practice block):* Sorting tasks 1 and 2 are combined for practice. Respondents use the left key for both **exact and natural sciences** concepts and male trait attributes, and the right key for both **human sciences** concepts and female trait attributes.

4. *Concept-attribute pairing (critical block):* Sorting tasks 1 and 2 are combined for generating critical data. Respondents use the left key for both **exact and natural sciences** concepts and male trait attributes, and the right key for both **human sciences** concepts and female trait attributes.

5. *Learning to switch the spatial location of the concepts:* Respondents sort stimuli words from **exact and natural sciences** and **human sciences** concepts into their superordinate categories, as in the first block, but the key assignment is reversed. They use the left key of the computer keyboard for **human sciences** concepts and the right key for **exact and natural sciences** concepts.

6. *Concept-attribute pairing (practice block):* Block 3 is repeated for practice. Respondents use the left key for both **exact and natural sciences** concepts and male trait attributes, and the right key for both **human sciences** concepts and female trait attributes.

7. *Concept-attribute pairing (critical block):* Block 4 is repeated, generating critical information. Respondents use the left key for both **human sciences** concepts and

male attributes, and the right key for both **exact and natural sciences** concepts and female attributes.

As suggested above, blocks 4 and 7 are the ones that provide critical information which will therefore be used to calculate the IAT effect. Table 11 summarizes the sequence of trial blocks in the gender-STEM IAT.

Table 11 – Sequence of trial blocks in the gender-STEM IAT

Block	Number of trials	Function	Items assigned to left-key response	Items assigned to right-key response
1	20	Practice	Exact and Natural Sciences concepts	Human Sciences concepts
2	20	Practice	Male attributes	Female attributes
3	20	Practice	Exact and Natural Sciences concepts + Male attributes	Human Sciences concepts + Female attributes
4	40	Test	Exact and Natural Sciences concepts + Male attributes	Human Sciences concepts + Female attributes
5	20	Practice	Human Sciences concepts	Exact and Natural Sciences concepts
6	20	Practice	Human Sciences concepts + Male attributes	Exact and Natural Sciences concepts + Female attributes
7	40	Test	Human Sciences concepts + Male attributes	Exact and Natural Sciences concepts + Female attributes

Source: Adapted from Nosek, Banaji and Greenwald (2002) and Nosek, Greenwald and Banaji (2005).

A list of example stimulus words for the concepts and attributes for our study is provided below, adapted from Nosek, Banaji and Greenwald (2002) [11]:

- *Exact and Natural Sciences:* math, engineering, physics, astronomy, chemistry, geology, statistics
- *Human Sciences:* Portuguese, literature, philosophy, history, sociology, pedagogy, journalism
- *Masculine:* brother, father, uncle, grandfather, son, he, him
- *Feminine:* sister, mother, aunt, grandmother, daughter, she, her

The participants should be given a brief explanation about the tasks they are about to perform and consent to their participation. They must be seated in front of the computer and follow the instructions on the screen. The IAT may be administered in any regular computer with basic software apparatus.

3.3.5 Scoring procedure: The IAT effect

The IAT effect is calculated using an algorithm that has evolved over the years to fit more properly to its theoretical and methodological characteristics, such as IAT correlations with explicit measures, IAT correlations with response latency[12] and sensitivity to known influences (GREENWALD; NOSEK; BANAJI, 2003). The

[11] These and other similar stimuli words cleared as descriptive of the concepts and attributes we are working with will be used in our study, with the proper adaptation to Portuguese.

[12] Response latency within social psychology is defined as the time interval between the presentation of a stimulus and the response of the subject (FAZIO, 1990).

improved algorithm by Greenwald, Nosek and Banaji (2003) gains in cost savings – by reducing the required sample size from 63 to 39 respondents, as well as construct purity, and it is less contaminated by extraneous variables than the conventional one[13].

Considering the points above, the procedure for obtaining the IAT measure has 9 steps:

1. Drop blocks 1, 2, 5 and 5. Therefore we use data from blocks 3, 4, 6 and 7.
2. Eliminate trials with latencies above 10,000 milliseconds, eliminate respondents for whom more than 10% of trials have latency below 300 milliseconds.
3. Compute mean of correct latencies for each block.
4. Compute pooled standard deviation for all trials in blocks 3 and 6; another for blocks 4 and 7.
5. Replace each error latency with block mean plus 600 milliseconds.
6. Average the resulting values for each of the 4 blocks.
7. Compute the following differences: block 6 - block 3 and block 7 - block 4.
8. Divide each difference by its associated pooled-trials standard deviation.
9. Average the quotients obtained in the last step.

3.3.6 IAT result analysis: ordered *probit*

After the scoring procedure of the IAT is complete, each respondent gets a objective result, ranging from categories that affirm the stereotypical views of gender and STEM to ones that are contrary to the stereotype. The existence of a categorization of the sort suggests the use of a ordered response model for the regression analysis of the IAT results. For that reason, we will apply an ordered probit model. This is an adequate approach, firstly, because of the ordinal nature of the results – the levels of implicit stereotype vary from stereotype congruent to stereotype incongruent, passing by a point of neutrality. Secondly, because such measures can be clustered into categories – in this case, a total of 3 (three).

In our model, we observe the measure of implicit stereotype, y. As with binary models, we are interested in knowing how changes in the predictors, x', translate into the probability of observing a particular ordinal outcome, which varies from 0 to 2. We begin with a latent variable y^*, that is, the implicit stereotype that is not observed. We define:

[13] The conventional IAT scoring algorithm produces spuriously extreme scores for respondents that take more time to make the associations (GREENWALD; NOSEK; BANAJI, 2003). See Greenwald, Nosek and Banaji (2003) for more advantages of the new algorithm

$$
\begin{aligned}
y = 0 \quad & \text{if} \quad y^* \leq \alpha_1 \\
y = 1 \quad & \text{if} \quad \alpha_1 < y^* \leq \alpha_2 \\
y = 2 \quad & \text{if} \quad y^* \geq \alpha_2
\end{aligned}
$$

where α_i is the threshold parameters for y^*. As a result, measured implicit stereotype, y will take the value (stereotype congruent, neutral or stereotype incongruent) associated with the latent implicit stereotype level, y^*. Generalizing the model according to Greene (2000), in an ordered model with m alternatives we define:

$$
y_j = j \qquad \text{if} \qquad \alpha_{j-1} < y_i^* \leq \alpha_j \tag{3.3.1}
$$

Therefore:

$$
\begin{aligned}
Pr[y_j = j] &= Pr[\alpha_{j-1} < y_i^* \leq \alpha_j] \\
&= Pr[\alpha_{j-1} < x_i'\beta + \mu_i \leq \alpha_j] \\
&= Pr[\alpha_{j-1} - x_i'\beta < \mu_i \leq \alpha_j - x_i'\beta \\
&= F(\alpha_{j-1} - x_i'\beta) - F(\alpha_j - x_i')
\end{aligned}
$$

where μ_i is the error, F is the cumulative density function of the error and β represents the coefficients to be estimated, so that we can infer the probability of observing a given implicit stereotype measure (as a function of the probability of a given interval of latent implicit stereotype). In this study, as well as in Braga (2018), we assume that y^* can be fitted into a linear regression model, such that $y^* = x_i\beta + \mu_i$, and that the errors are normally distributed. Consequently, the maximum likelihood estimation results in ordered probit parameters.

We are also interested in measuring the marginal effects, given by:

$$
\frac{\partial Pr[y_j = j]}{\partial x_i} = \{F'(\alpha_{j-1} - x_i'\beta) - F'(\alpha_j - x_i')\}\beta \tag{3.3.2}
$$

By computing the estimates for the marginal effects, it is possible to measure the percentage points associated with each measure of observed implicit stereotype, for each independent variable in the model.

3.4 Experiment results

The gender-STEM IAT, designed to measure the implicit gender stereotype in STEM fields, was made available to all students of Universidade Federal de Viçosa during the month of November, 2019, via a link[14] sent to the institutional e-mail of each student, accompanied by a short description of the scope of the research and the instructions to complete the test. The test was preceded by a questionnaire where students fill out information such as their gender and their course, as well as respond to questions about their perceptions about gender stereotypes[15], which we used to construct the *explicit* measure of gender-STEM stereotype.

Subsequently, the respondents were introduced to the IAT and received the specific instructions to successfully complete the test. Their responses were computed according to the algorithm presented in the Methodology section, and categorized in 1 of 9 groups, corresponding to levels of stereotype, ranging from congruent to incongruent. This constitutes the *implicit* measure of gender-STEM stereotype. All incomplete responses were dropped. The results are organized in two parts – descriptive analysis and ordered *probit* analysis.

3.4.1 Descriptive analysis

We received 552 complete responses to both the questionnaire and the IAT. We then excluded 175 observations, of which 161 correspond to graduate students. Moreover, 6 deletions correspond to undergraduate courses which are not taught at UFV. In addition, 8 were deleted either because they filled out the age box incorrectly or because they were outliers, which can be a source of bias. Therefore, our analysis will be based on responses from 377 undergraduate students in the university.

We grouped the students according to knowledge or scientific fields from the Coordination for Higher Education Staff Development (CAPES), an institution responsible for the quality of higher education in Brazil. The distribution is presented in Table 12, below, together with the distribution by reported gender:

According to Table 12, the areas with the higher proportion of women respondents, relative male respondents, are Human Sciences, Applied Social Sciences, Health Sciences, Agricultural Sciences and Biological Sciences. We did not consider Arts and Language because it has only one observation. Overall, 54,6% of respondents were women, and they represent around 37% of students in Engineering and Exact Sciences.

To avoid working with groups too small to get valid statistics, we clustered related areas – biological sciences with health sciences, human sciences with arts and language, and engineering with exact sciences (broadly, the STEM field), so that we are left with 5 broad fields.

[14] http://tai.nobugs.com.br/

[15] All questions were approved by the Ethics Committee of the university. The complete questionnaire is available in the Appendix.

Table 12 – IAT respondents distributed among scientific fields and reported gender.

Scientific Field	**Female**	**Male**	**Total**	**Female Percentage**
Agricultural Sciences	37	28	65	56,9%
Biological Sciences	15	13	28	53,6%
Engineering	31	45	76	40,8%
Exact Sciences	13	29	42	31,0%
Human Sciences	32	13	45	71,1%
Arts and Language	1	0	1	100,0%
Health Sciences	16	12	28	57,1%
Applied Social Sciences	61	31	92	66,3%
Total	**206**	**171**	**377**	**54,6%**

Source: IAT results.

3.4.1.1 Explicit stereotype measure

When respondents were asked with which intensity they associate exact and natural sciences with men and women, they chose from a scale that went from strongly masculine to strongly feminine. Among female respondents, 40,8% said that they do not differentiate, that is, they are neutral. Among male respondents, that percentage was bigger – 49,8%. Not one male respondent associated STEM with feminine, and only 7 (3,4%) of women did so. On the other end of the scale, 55,8% of women and 50,3% of men associated STEM with masculine, mostly *slightly* or *moderately*. Therefore, the majority of students, men and women, responded in conformity to the gender-STEM stereotype.

When respondents did the same associations for human sciences, the proportion of neutral associations were higher – 57,8% among women and 63,2% among men. According to their answers, human sciences are less stereotypically perceived than exact and natural sciences are. Nonetheless, the associations between human sciences and the feminine concept are significant – 35% of women and 31,6% of men think that human sciences are, to some degree, a feminine field. Oppositely, 7,3% of women and 5,3% of men think that it is a masculine field.

The thermometer measure for explicit stereotype is a combination of both the associations above, which are summarized in Figure 7. The more an individual associates STEM with masculine *and* human sciences with feminine, the more stereotype congruent the explicit measure is. If the contrary happens, we have a stereotype incongruent measure. We can also have a neutral position, where a person does not associate either field with masculine or feminine valences. In the present experiment, 67% of the women who participated belong in the latter category, and the same is true for 63,7% of the men. While there exists some variation between scientific fields, at least half of men and women across all fields fall into this category, with the exception of men in biological sciences, where they represent 48%.

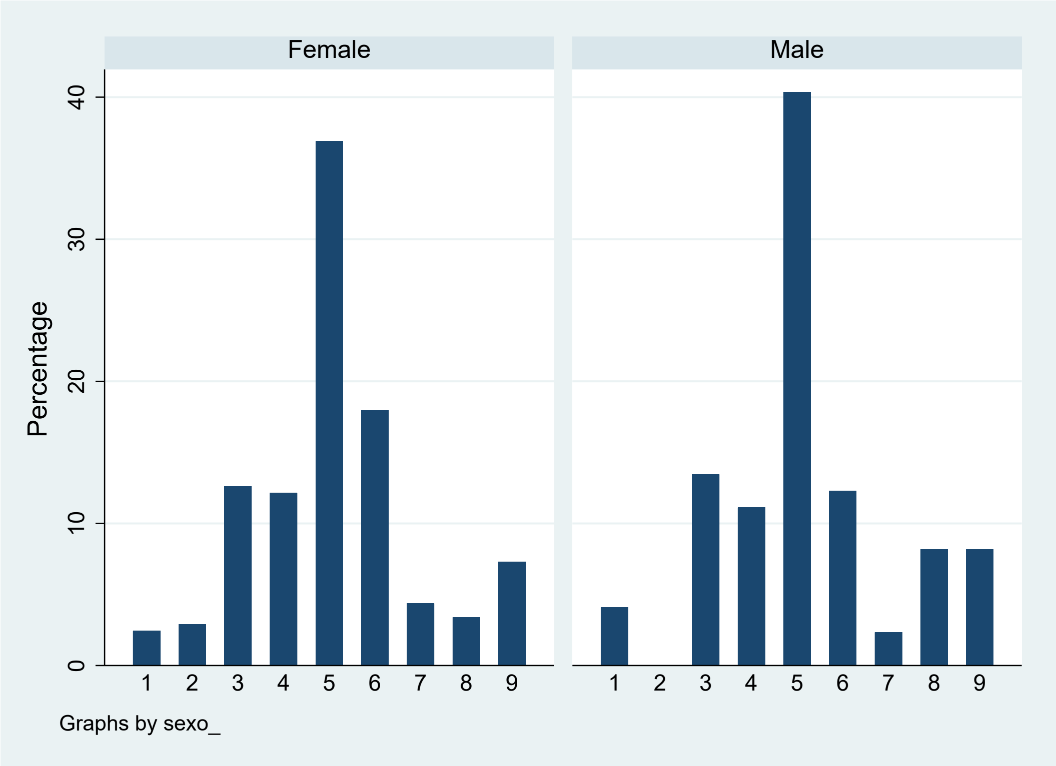


Figure 7 – Explicit measure of gender-STEM stereotype at UFV – distribution by gender.

Note that, at Figure 7, the stereotype congruent categories are the smaller numbers, varying from 1 to 3. The neutral category is represented by the central area of the graph, where respondents are concentrated (4 to 6). Lastly, the stereotype incongruent category is on the right side of the chart, from 7 to 9.

Overall, we did not observe systematical differences, even controlling for gender and field of study. This is not true for the implicit measure, as we will see below. For that reason, we found a low correlation between explicit and implicit measures.

3.4.1.2 Implicit stereotype measure

The results that follow are based on the codes and respective meanings summarized by Table 13 for the implicit measure of stereotype. These are the results that represent the possible outcomes for each participant who took the IAT. As with the explicit measure, they vary from 1 to 9, ranging from a stereotype congruent outcome to an incongruent one. Moreover, Tables 14 and 15 represent the distribution of female and male students from UFV among IAT results and scientific fields.

According to Table 14, the 206 female respondents are relatively evenly distributed among fields, with proportions ranging from 15% (biological) to 30% (applied social). Moreover, we see that 45% of all women in the sample are in the most stereotype-congruent

Table 13 – IAT results and their respective codes for use in the ordered probit estimation.

Code	Meaning
1	You associate men with exact and natural sciences and women with human sciences much more than men with human sciences and women with exact and natural sciences
2	You associate men with exact and natural sciences and women with human sciences more than men with human sciences and women with exact and natural sciences
3	You associate men with exact and natural sciences and women with human sciences a little more than men with human sciences and women with exact and natural sciences
4	You associate men with exact and natural sciences and women with human sciences slightly more than men with human sciences and women with exact and natural sciences
5	You don't associate men with exact and natural sciences any more than you associate women with exact and natural sciences
6	You associate women with exact and natural sciences and men with human sciences slightly more than women with human sciences and men with exact and natural sciences
7	You associate women with exact and natural sciences and men with human sciences a little more than women with human sciences and men with exact and natural sciences
8	You associate women with exact and natural sciences and men with human sciences more than women with human sciences and men with exact and natural sciences
9	You associate women with exact and natural sciences and men with human sciences much more than women with human sciences and men with exact and natural sciences

Source: Based on Project Implicit (2011), with modifications.

Table 14 – Distribution matrix of *female* students according to IAT results and scientific field.

Code	**Scientific Field**					
	Agricultural	**Biological**	**Exact**	**Human**	**Applied Social**	**Total**
1	8%	6%	5%	11%	15%	45%
2	0%	0%	0%	1%	1%	2%
3	1%	2%	2%	1%	2%	9%
4	0%	0%	0%	0%	0%	0%
5	5%	5%	6%	1%	8%	26%
6	1%	0%	1%	0%	0%	3%
7	1%	0%	0%	0%	0%	2%
8	0%	0%	0%	0%	1%	1%
9	0%	1%	6%	0%	2%	11%
Total	18%	15%	21%	16%	30%	100%

Source: IAT results.

category, meaning that they associate men with exact and natural sciences and women with human sciences much more than men with human sciences and women with exact and natural sciences. These women are concentrated in the areas of human and applied social sciences.

On the other end of the spectrum, we observe that 11% of female students associate women with exact and natural sciences and men with human sciences much more than woman with human sciences and men with exact and natural sciences. That is, they make implicit associations that are contrary to stereotypical views of gender, math and science. The majority of these women are majoring in exact sciences, a fact that is expected if it is true that gender-STEM stereotypes negatively correlate with the choice of math-intensive majors by women.

Note that the implicit views of 26% of women in the sample are categorized as neutral, which means that they do not associate men with exact and natural sciences any more than they associate women with exact and natural sciences. These respondents occur more in applied social sciences, and less in human sciences.

Table 15 – Distribution matrix of *male* students according to IAT results and scientific field.

Code	**Scientific Field**					
	Agricultural	**Biological**	**Exact**	**Human**	**Applied Social**	**Total**
1	11%	8%	25%	3%	10%	57%
2	1%	0%	2%	1%	0%	3%
3	1%	1%	2%	0%	0%	4%
4	0%	0%	0%	1%	0%	1%
5	3%	5%	9%	2%	6%	25%
6	0%	1%	0%	1%	1%	3%
7	0%	0%	2%	1%	1%	3%
8	0%	0%	1%	0%	0%	1%
9	1%	1%	2%	0%	1%	5%
Total	16%	15%	43%	8%	18%	100%

Source: IAT results.

According to Table 15, among 171 male respondents the distribution of IAT results are similar to the ones of Table 14, although there is a steeper tendency towards stereotypical views among men, in comparison to women. Moreover, the general distribution of men between scientific fields display more variation, ranging from 8% (human sciences) to 43% (exact sciences). Note that among male students with strong stereotypical views (category 1), 44% of them major in an exact sciences course.

3.4.2 Ordered *probit* analysis

To test the hypothesis that women in exact sciences have a smaller average degree of implicit stereotype, we conduct an ordered *probit* analysis for the sample of 206 female undergraduate students. Seeing that there are few results in Table 14 that are not either in the extreme categories or in the neutral area, we clustered the less populated categories such that we are left with 3 groups: 1-2-3, 4-5-6 and 7-8-9. Respectively, these correspond to stereotype congruent, neutral, and stereotype incongruent clusters.

For the purposes of the *probit* model, we have a dependent ordinal variable, the stereotype cluster, varying from 0 to 2. The independent variables are *dummies* for knowledge areas, namely *Exact*, *Agricultural*, *Biological* and *Human*. The variable for applied social sciences is omitted because of collinearity. The results are organized in Table 16.

Table 16 – Ordered *probit* analysis for IAT results of female students.

Scientific field	**Coefficient**	**Standard error**
Exact	0,73	0,23
Agricultural	0,05*	0,24
Biological	0,16*	0,26
Human	-0,78	0,30

Source: IAT results. Note: (*) denotes coefficients that were not statistical significance at 5%.

By looking at the direction of the effects in Table 16, we observe that it is more likely for a student to be in stereotype incongruent group if she studies an exact science (+). Conversely, there is a higher probability associated with being in the stereotype congruent category if the student is a human sciences major (-). We can derive more direct interpretations by computing the marginal effects, exhibited in Table 17.

Table 17 – Marginal effects of ordered *probit* analysis for IAT results of female students.

Field	**Stereotype congruent**	**Neutral**	**Stereotype incongruent**
Exact	-0,26	0,11	0,15
Agricultural	-0,02*	0,01*	0,01*
Biological	-0,06*	0,02*	0,03*
Human	0,28	-0,12	-0,16

Source: IAT results. Note: (*) denotes coefficients that were not statistical significance at 5%.

According to Table 17, being in the exact sciences field additively increases the probability of being in the stereotype incongruent category by 15 percentage points. Similarly, the same position decreases the probability of being in the stereotype conforming group by 26 percentage points. Note that being in the human sciences field is associated with almost exactly the opposed result – it additively increases the chance of conforming to the stereotype in 28 percentage points, and diminishes the probability of non-conformance to stereotype by 16 percentage points.

Therefore, we have evidence indicating that stereotypical views of women – specifically regarding science, technology, engineering and math stereotypes – are negatively correlated with the choice of STEM majors by women at Universidade Federal de Viçosa. Note that we cannot derive a causal relationship from our results. Nonetheless, we observe that women in exact sciences are less likely to show gender-STEM stereotype, compared to women in human sciences[16]. This means that women in the human sciences field implicitly associate men more with STEM and women more with humanities.

The literature suggests that men do the same associations (NOSEK; BANAJI; GREENWALD, 2002), regardless of the field they study. However, the coefficients we estimated were not statistically significant for the sample of men. It is likely that this result is a function of the fact that we do not observe variation between scientific fields – the majority of men in *all* fields, associate men more with STEM and women more with humanities. With the exception of men in human sciences, that association is *strong*.

3.5 Concluding remarks

The objective of this study was to identify the existence and analyse the gendered distribution of gender stereotypes in the STEM field in Brazil. Motivated by that, we conducted a social-psychological experiment at Universidade Federal de Viçosa (UFV) in Southeastern Brazil, in which we applied the gender-STEM Implicit Association Test (IAT) and employed the ordered *probit* analysis.

We found that women in STEM are less likely to show gender-STEM implicit stereotype, compared to women in humanities. In other words, they are more likely to belong in the incongruent stereotype end of the spectrum, while women in human sciences are more likely to implicitly conform to the stereotype.

The main challenge we faced regarded the sensitivity of the subject – gender stereotypes are complicated both to approach and to measure. Nonetheless, we were able to design an innovative procedure, from the choice and adaptation of the instrument to the qualitative analysis we implemented.

The results we found indicate that there is a negative correlation between implicit

[16] The interpretation of the IAT results as indicators of implicit stereotype is supported by the theoretical definition of the construct and the associations between concept and attributes, such as defined by (GREENWALD; NOSEK; BANAJI, 2003) and described in the theoretical framework.

gender stereotyping and the the choice of math-intensive majors by women at UFV. We did not find relevant differences in men across scientific fields – in every field, we found that men associate men more with STEM and women more with humanities, a stereotype congruent result. In this sense, the fact that most of our subjects displayed stereotype-congruent results is indicative of the profoundness of gender bias in Brazilian society.

While we can not say that the instrument we used can predict behaviors, in this study the gender-STEM IAT has been useful in demonstrating the correlation of an important aspect of "gender culture" (gender stereotypes) and the gender composition of STEM fields. This gives some insight into how individuals assimilate aspects of gender bias into their everyday lives – each to a higher or lower degree – culminating in life-defining choices.

For future researches, we suggest the use of other experiment designs and instruments to help substantiate the findings.

3.A Appendix – Experiment questionnaire

Este questionário faz parte da pesquisa "Estereótipos de gênero e escolha ocupacional na Universidade Federal de Viçosa". Sua resposta às questões que se seguem são sigilosas e você não será identificado(a). Os riscos e benefícios provenientes da resposta a esse questionário estão de acordo com o explicitado no Termo de Consentimento Livre e Esclarecido (TCLE).

1. Qual o seu sexo?
   (a) Feminino
   (b) Masculino
   (c) Outro

2. Como você classifica a sua identidade de gênero?
   (a) Se identifica fortemente com o masculino
   (b) Se identifica moderadamente com o masculino
   (c) Se identifica levemente com o masculino
   (d) Sem diferença na identificação com o masculino e o feminino
   (e) Se identifica levemente com o feminino
   (f) Se identifica moderadamente com o feminino
   (g) Se identifica fortemente com o feminino

3. Qual o seu curso?
   (Lista de todos os cursos de graduação e pós-graduação da UFV)

4. Em qual período você está?

5. Qual a sua idade?

6. Qual a sua cor?
   (a) Preta
   (b) Branca
   (c) Parda
   (d) Amarela
   (e) Indígena
   (f) Outra

7. Por favor, avalie o quanto você associa Ciências Exatas e Naturais com homens e mulheres:
   (a) Fortemente masculino
   (b) Moderadamente masculino
   (c) Ligeiramente masculino
   (d) Nem masculino nem feminino
   (e) Ligeiramente feminino
   (f) Moderadamente feminino
   (g) Fortemente feminino

8. Por favor, avalie o quanto você associa Ciências Humanas com homens e mulheres:
   (a) Fortemente masculino
   (b) Moderadamente masculino
   (c) Ligeiramente masculino
   (d) Nem masculino nem feminino
   (e) Ligeiramente feminino
   (f) Moderadamente feminino
   (g) Fortemente feminino

9. Por favor, avalie sua atitude com relação às Ciências Exatas e Naturais:
   (a) Gosto muito
   (b) Gosto
   (c) Não gosto nem desgosto
   (d) Desgosto
   (e) Desgosto muito

10. Por favor, avalie sua atitude com relação às Ciências Humanas:
    (a) Gosto muito
    (b) Gosto

(c) Não gosto nem desgosto
(d) Desgosto
(e) Desgosto muito

11. Existem menos mulheres que homens professores(as) em cursos de graduação de Ciências Exatas e Naturais em universidades prestigiadas. Os fatores que se seguem são muitas vezes citados como razão dessa diferença. Na sua opinião, o quão importante é cada fator na explicação dessa diferença.

    11.1. Em média, homens e mulheres diferem na sua disposição em empregar o tempo exigido por essas carreiras de prestígio.
    (a) Extremamente importante
    (b) Muito importante
    (c) Pouco importante
    (d) Ligeiramente importante
    (e) Sem importância

    11.2. Em média, homens e mulheres diferem na sua disposição em passar tempo longe de suas famílias.
    (a) Extremamente importante
    (b) Muito importante
    (c) Pouco importante
    (d) Ligeiramente importante
    (e) Sem importância

    11.3. São encontradas diferentes proporções de homens e mulheres entre as pessoas com maiores níveis de habilidade matemática.
    (a) Extremamente importante
    (b) Muito importante
    (c) Pouco importante
    (d) Ligeiramente importante
    (e) Sem importância

    11.4. Em média, homens e mulheres diferem naturalmente nos seus interesses científicos.
    (a) Extremamente importante
    (b) Muito importante
    (c) Pouco importante
    (d) Ligeiramente importante

(e) Sem importância

11.5. Direta ou indiretamente, meninos e meninas tendem a receber níveis diferentes de encorajamento para desenvolver seus interesses científicos.
(a) Extremamente importante
(b) Muito importante
(c) Pouco importante
(d) Ligeiramente importante
(e) Sem importância

11.6. Em média, consciente ou inconscientemente, os homens são favorecidos em contratações e promoções.
(a) Extremamente importante
(b) Muito importante
(c) Pouco importante
(d) Ligeiramente importante
(e) Sem importância

12. Classifique o quanto é importante, na sua opinião:

12.1. Ser competente em ciência.
(a) Extremamente importante
(b) Muito importante
(c) Pouco importante
(d) Ligeiramente importante
(e) Sem importância

12.2. Ser competente em matemática.
(a) Extremamente importante
(b) Muito importante
(c) Pouco importante
(d) Ligeiramente importante
(e) Sem importância

12.3. Ser competente em ciências humanas.
(a) Extremamente importante
(b) Muito importante
(c) Pouco importante

(d) Ligeiramente importante

(e) Sem importância

4 CONCLUSION

The objectives of this research were to analyse the structure of the math-gender gap in Brazil, uncovering the subjective, gender-specific factors associated with it and to analyse if stereotypical views of women are connected to the choice of math-intensive majors by women.

To that end, in the first essay we employ an Oaxaca-Blinder detailed decomposition to investigate how the gender gap measured by math achievement functions by looking at different schooling levels (primary and secondary) and in different points of the math score distribution. We find that most of the math-gender gap is due to its unexplained, non-observable component, and that it increases with level of education and with test performance.

We argue to those non-observable gender differences are at least partially connected to gender stereotypes. By understanding that the math-gender gap intensifies with age and by assuming that it culminates in the under-representation of women in the STEM field (for which the literature provides evidence), we then perform a social experiment to test the hypothesis that stereotypical views of women are negatively correlated with the choice of STEM majors by women. This is the subject of our second essay.

Thus, in the second essay we employ our adaptation of the Implicit Association Test, the gender-STEM IAT, to measure individual implicit gender stereotypes in STEM. We find that women in STEM are less likely to associate *men* with *STEM*, compared to women in humanities, and to men. Among men, specifically, we found that males of every field associate *men* more with *STEM* and *women* more with *humanities*. These results are indicative of the pervasiveness of gender-stereotypes in Brazilian society. They are probably better understood as a social phenomena than simply individual bias[1].

Overall, through our evidence and evidence-based assumptions, we are able to demonstrate that, as individuals age and assimilate society-imposed gender roles, they are subscribed to gender-specific educational paths (such as the dis-identification of women with math) and, inevitably, occupations (STEM field). Women who depart from the stereotype may do so because of some combination of their innate ability, opportunity, and, as we have seen, their more nuanced assimilation of gender stereotypes. However, this specific mechanism needs more exploration to be better understood, and a bigger sample in order to be generalized for Brazil.

Our findings give supporting evidence to the idea that policy designs to promote gender equity in the distribution of occupations should be multidimensional. It is,

[1] See Hinton (2017) for an elaboration of this thought.

evidently, important to support girls who show interest and ability in math, and give visibility and support to the existent initiatives, such as *ELAS nas exatas* (FUNDO. . . , 2020), *PrograMaria* (PROGRAMARIA, 2020), *Torneio Meninas na Matemática* (TM2, 2020), among others. Moreover, it seems necessary to integrate gender equity principles into formal education, seeing that math and STEM gender stereotypes is an ever-present reality – with long-lasting impacts – in the lives of children and young adults who spend a significant part of their days in school. These initiatives may occur in the form of seminars and interventions, and they can (and possibly do) happen through the same programs that support girls. Finally, better results could be achieved with extensive orientation for parents with small children, seeing that parents help shaping their children's self-perception and self-esteem, which in turn may influence how kids, particularly girls, relate to societal pressures for subscription to gender roles.

For future research, we recommend the extension of this framework to analyse the intersection between gender and color/ethnicity, seeing that color is, in Brazil, deeply detrimental to social equity, specially at its intersection with gender.

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