

New evidence on the gender gap in mathematical achievement in Brazil

Evidências sobre as disparidades de gênero no desempenho em matemática nas escolas brasileiras

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Resumo

Os índices de desempenho matemático nos países sul-americanos são piores que o dos países desenvolvidos e os estudantes brasileiros possuem os piores *scores*, sendo que os garotos possuem vantagem sobre as meninas em todas as idades. Neste trabalho, demonstramos que os efeitos não observáveis são decisivos para explicar as diferenças de gênero no desempenho matemático nas escolas brasileiras. Utiliza-se de modelos de decomposição quantílica para observar os efeitos de gênero individuais e contextuais. As diferenças médias observadas são parcialmente função de vieses de gênero socialmente construídos. Ainda, encontramos que as diferenças de desemprenho por gênero persistem pela educação primária e secundária e aumentam nas séries mais velhas. Estas diferenças não são explicadas por características individuais e familiares, mas principalmente por fatores não observados.

Palavras-chave: *Desempenho matemático. Gap de gênero. Decomposição de desigualdades. Brasil.*

Abstract

South American countries have some of the worst overall achievement scores in math compared to developed countries. Brazilian students have the lower relative score which boys outperform girls in all ages. In this work we aim to demonstrate that gender plays a decisive role in the difference in math achievement in Brazil. We performed an Oaxaca-Blinder decomposition of the math-gender gap in unconditional quantiles in order to measure which proportion can be attributed to actual gender differences in converting individual and contextual characteristics into math achievement. The average differences we observed are partially a function of socially constructed gender roles and stereotypes, which may affect each individual differently. Nevertheless, we found that gender differences in math achievement persist across primary and secondary education (increasing with school-grade), and they are not explained by individual, family and school characteristics, but mostly by unobservable gender differences in returns to these characteristics.

Keywords: *Mathematical achievement. Gender gap. Inequality decomposition. Brazil.*

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Initial remarks

South American countries have some of the worst overall achievement scores in math, according to the Programme for International Student Assessment (PISA) (Organization 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-yearold students math is the subject with the lower relative score, similar to 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 the 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 (OECD, 2018).

Several studies about the gender gap in math achievement were conducted in other countries: Fryer Junior & Levitt (2010, p. 213) 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 et al. (2017) demonstrated that girls systematically under-perform boys and that the differential is larger among top performing children. In Kenya, Ng'ang'a et al. (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 (2004) conclude that the gap in mathematical achievement is slightly significant and increasing in school grade. Finally, Andrade et al. (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 & Jones (1993, p. 100), states that "[…] socialization follows social structure", and so, that gender differences in opportunity supported by society can affect mathematical achievement and attitudes. Gevrek et al. (2020, p. 19) 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 & 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, p. 1165) 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 socialpsychological approach, Nosek et al. (2009) concluded, in a cross-country analysis, that implicit gender stereotypes are highly correlated with gender differences in math achievement.

In this sense, Greenwald & 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 ob- serve 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, as detailed below.

In an effort to explore the math gender gap using country-specific survey data, studies such as Sohn (2012), Gevrek & Seiberlich (2014) performed their versions of an inequality decomposition of gender differences. They decomposed the gap into observable and unobservable parts, and found that, in the United States, there are distribution-specific 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, p. 35). 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 (WEF, 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.

Identification strategy

Addressing causal effects for gender gaps is a tricky task since the disparities be- tween 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 gen- der 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:

 $R = E_i \left[Y_{\rho} \right] - E \left[Y_h \right]$ (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:

$$
Y_i = X\beta_i + \epsilon_i \tag{2}
$$

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

$$
Y_g - Y_b = \left[X_b \left(\beta_g - \beta_b \right) \right] + \left[\left(X_g - X_b \right) \beta_g \right] \tag{3}
$$

Specifically, as explained by Fortin et al. (2011), let *Di* represent a dummy for the student's gender, and taking the expectations over *X*, the overall score gap can be represent by:

$$
\Delta_O^{\mu} = E \Big[Y_g \mid D_g = 1 \Big] - E \Big[Y_b \mid D_g = 0 \Big] \tag{4}
$$

$$
=E\left[E\left(Y_g|X,D_g=1\right)|D_g=1\right]-E\left[E\left(Y_b|X,D_g=0\right)|D_g=0\right]
$$
\n⁽⁵⁾

$$
= (E[X \mid D_g = 1]B_g + E[J_g \mid D_g = 1]) - E[X \mid D_g = 0]B_b + E[J_b \mid D_g = 0])
$$
\n⁽⁶⁾

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

$$
\Delta_O^{\mu} = \mathbb{E}\left[X \mid D_g = 1\right]\beta_g - E\left[X \mid D_g = 1\right]\beta_b + E\left[X \mid D_g = 1\right]\beta_b - E\left[X \mid D_g = 0\right]\beta_b\tag{7}
$$

$$
=E[X \mid D_g=1] \left(\beta_g - \beta_b\right) + \left(E\left[X \mid D_g=1\right] - E\left[X \mid D_g=0\right]\right)\beta_b\tag{8}
$$

$$
= \hat{\mathbf{A}}_S^{\mu} + \hat{\mathbf{A}}_X^{\mu} \tag{9}
$$

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

$$
\hat{\Delta}_{O}^{\mu} = \overline{X}_{g} \hat{\beta}_{g} - \overline{X}_{g} \hat{\beta}_{b} + \overline{X}_{g} \hat{\beta}_{b} - \overline{X}_{b} \hat{\beta}_{b}
$$
\n(10)

$$
= \overline{X}_{g} \left(\hat{\beta}_{g} - \hat{\beta}_{b} \right) - (\overline{X}_{g} - \overline{X}_{b}) \hat{\beta}_{b}
$$
\n
$$
\tag{11}
$$

$$
=\hat{\Delta}_S^{\mu} + \hat{\Delta}_X^{\mu} \tag{12}
$$

In the above equation, $\hat{\Delta}^\mu_S$ are the gender-return effects and $\hat{\Delta}^\mu_X$ 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, p. 141), 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 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 a 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 & Bassett Junior (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):

$$
RIF(Y; q\tau) = q\tau \frac{\tau - \mathbb{I}\{Y \leq q_{\tau}\}}{f_Y(q_{\tau})}
$$
\n(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_r ; $f_Y(q_r)$ 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:

$$
\alpha(\tau) = c_{1,\tau} \left[Y > q \mid X = x \right] \, dx \, dFX(x) \tag{14}
$$

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.

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 et al., 2014). The variable descriptions are given in Table 1.

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

Table 1. Variable descriptions.

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 totaling 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 (INEP, 2016).

In addition to the test, each student receives a questionnaire 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 di- rectors 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.

Missing data approach

According to Vinha & Laros (2018), studies who use data from educational sur- veys in Brazil rarely report missing values. In the cases they did, the treatment applied was usually deletion of observations that were missing data1. For all variables tested for missing values in the sample, there was a difference in average math score between re- spondents 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 variable². It is also the case that the overwhelming majority of survey non-response – 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 deletion³ 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.

Results

Descriptive statistics

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

¹ See Vinha & Laros (2018) for a list of studies who reported missing data from education databases and their respective treatment strategies.

² 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 math scores, in comparison to those that responded.

³ 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*.

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 is 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. 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 math scores, in comparison to those that responded.

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

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

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

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

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

Table 4. Descriptive statistics by gender - high school.

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

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 et al., 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

Figure 1. Math achievement distribution by gender.

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 A.1-3 in Appendix A, 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 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 gen- der gap across grades. What is more, it operates in different directions – in fifth grade, con- trolling 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

Table 5. Unconditional quantile regression results for fifth, ninth and third (high school) grades.

Notes: *** p<0.001, ** p<0.05, *p<0.1. Robust standard errors in parenthesis.

inserted in school environments that accentuate their disadvantage to boys. The descriptive statistics (Table 4) as well as the extended results in Appendix A (Table A.3) 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.

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 et al. (1990), Fryer Junior & Levitt (2010), Bharadwaj et al. (2016). Through all ages, the descriptive statistics

Figure 2. The gender gap in each quantile.

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

(c) High school

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

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 et al., 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.

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.

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 family 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 an 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 A.4 and A.5 in Appendix A.

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

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 analyzed 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 an 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,

(c) High school

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

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 re- turns 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 disidentification of women with math, which in turn tends to reinforce the underrepresentation 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.

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None.

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

