Girls vs. Boys: Who is Dropping Out of School Because of Bullying?

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Abstract

Despite the rising interest in the problem of bullying, there is little evidence about its effects on dropping out of school, and this evidence is affected by the problem of omitted variable bias. To understand the effect of bullying on dropping out of school, I exploit a rich data set of adolescents between 13 and 17 years old from families that participate in the Mexican conditional cash transfer program PROGRESA. Boys experience higher rates of bullying than girls, but bullying affects only girls' probability of dropping out of school. In particular, a one standard deviation increase of being bullied raises girls' probability of dropping out of school by 5 percentage points. To address the problem of omitted variables, I implement a bounding strategy following Oster (2017). In addition, I conduct an instrumental variable approach following Lewbel (2012). The bounding and instrumental variable strategies suggest that this result is robust to omitted variable bias.

Keywords: education; bullying; adolescents; gender

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1 Introduction

Bullying is a problem that permeates many countries around the world. It ranges from 9 percent in Italy to 74 percent in Samoa among adolescents between 13 and 15 years old (Unicef, 2014). Alarmingly, bullying has been associated with growing levels of depression (Ttofi et al., 2011), problems of low self-esteem (Kopasz and Smokowski, 2005), and with declines in academic performance (Nakamoto and Schwartz, 2010). Despite the overall negatives effects of bullying on adolescents' well-being, there is little research about its effects on dropout rates in schools.

To understand the effect of bullying on the probability of dropping out of school, I exploit a rich data set of adolescents between 13 and 17 years old from families that participated in the Mexican conditional cash transfer program PROGRESA. The results show that boys experience higher rates of bullying than girls, but bullying presents consequences exclusively for dropping out of school for girls. In particular, a one standard deviation increase in being bullied raises the probability of girls' dropping out of school by 5 percentage points. As a robustness test for omitted variable bias, I use a bounding strategy following Altonji et al. (2005) and Oster (2017). In addition, I conducted an instrumental variable approach following Lewbel (2012). The bounding and instrumental variable strategies suggest that the result is robust to omitted variable bias.

To the best of my knowledge, there are only two papers that analyze the relationship between bullying and dropping out of school. Cornell et al. (2013), using data from 276 Virginia public schools in the United States, suggest that one standard deviation increase in being bullied is associated with 16.5% increase in the number of dropouts. Townsend et al. (2008), using data from 1,470 students in Cape Town, South Africa, find that when facing bullying, girls - but not boys - are more likely to drop out of school.[1] While these papers control for several well-known variables related with dropping out of school, their results could potentially be biased as a consequence of important omitted variables affecting both bullying and dropping out of school. For example, factors related with the adolescents' personality can help them cope with - an even minimize - bullying, but this information is not completely observed in the data.

This paper contributes to the literature showing that bullying has important consequences for dropping out of school. In particular, I find that bullying increases the dropout rate of girls, but not of boys, and that these results are robust to the problem of omitted variable bias. This finding supports the "gender paradox effect" of bullying proposed by Loeber and Keenan (1994). The gender paradox

[1]In particular, using a logistic regression, they report an odds ratio of 2.60

effect establishes that boys experience higher rates of bullying than girls, but bullying affects more negatively the well-being of girls than that of boys.

The rest of the paper is organized as follows: Section 2 reviews the related literature; Section 3 introduces the data and the empirical strategy; Section 4 presents the results; and Section 5 concludes.

2 Can Bullying Affect School Outcomes Based on Gender?

There is an important literature that points to the benefits of attending school, but we know little about its unintended consequences. Hansen and Lang (2011) propose that attending school can have some negative consequences for the mental health of students. In particular, they show that during the months when students tend to be on break from school (June, July, August, and December), youth suicide is significantly lower than the rest of the year in the US. More interestingly, the effect was bigger among female students than among their male counterparts. In particular, they found that suicides decline by 22 percentage among female 14- trough 18-year-olds and by 16 percentage for male 14- trough 18-year-olds.

They relate this situation to the increased *stress* that students face throughout the school.

What are the factors that cause *stress* in students within schools? One of the sources of stress may be negative social interactions associated with bullying. When exploiting state-level variation in anti-bullying laws in the United states, Rees et al. (2020)found that said laws are associated with a 13-16 percent reduction in the suicide rate of female 14- trough 18-years-olds, and no effect was found on their male counterparts. This result confirms the hypothesis that bullying can be one of the causes behind stress in students. Yet, it affects more girls than boys. Thus, the anti-bullying laws protect females, but not their male counterparts from suicide.

The previous results present some evidence that bullying is one of the factors that can generate stress among students and even escalate the problem to suicide. Yet, the question that remains open is why bullying potentially affects more girls than boys. Loeber and Keenan (1994) propose that there is a "gender paradox effect" of bullying such that boys experience higher rates of bullying than girls, but that bullying affects more negatively the well-being of girls rather than boys. Some of the hypotheses that try to explain why this gender paradox emerges are the following: (1) social networks, (2) coping mechanisms, and (3) verbal skills. The social network hypothesis states that females generate close and strong relationships among friends whereas males create larger and more diffuse social networks (Lagerspetz et al., 1988). Consequently, females tend to have more concern for interpersonal problems. Thus, when interpersonal problems emerge as a result of bullying, it affects girls more than boys. In accordance with the coping mechanism hypothesis, there are some gender differences regarding copying mechanisms (Athanasiades and Deliyanni-Kouimtzis, 2010). In particular, Athanasiades and Deliyanni-Kouimtzis (2010) analyze how males and females feel about bullying. They found that males tended to fail to recognize the negative effects of bullying and tended to justify bullying as a joke. On the other hand, females expressed their disapproval of bullying and recognized the negative effects on the victim. Finally, the verbal skills hypothesis proposes that females acquire verbal skills at an earlier stage than males (Bjorkqvist et al., 1992). The problem is that one of the principal manifestations of bullying is through verbal abuse, thus the verbal skills acquired at an earlier stage by females facilitate aggression. To sum up, this literature suggests that, when analyzing the effects of bullying on school outcomes, gender should be taken into account.

3 Data and Empirical Methods

3.1 Description of Data

To examine the effects of bullying on dropping out of school, I use a cross-sectional database that was collected in September 2012 with the purpose to analyze socioeconomic and non-cognitive skills of adolescents living in poverty, who participated in Mexico's PROGRESA conditional cash transfer program (Survey of Resilience and Social Mobility).[2] The survey collected information on non-cognitive skills of adolescents and their parents. A random sample of 2,112 households was selected among families participating in the program in both rural and urban areas. In the case of adolescents, it was decided to collect information among population between 13 and 17 years old. The survey collected information from 1,091 of these adolescents, who lived in 837 households. Two children who never went to school were excluded, so the final sample for this study was 1,089 adolescents.

Of these 1,089 young people between the ages of 13 and 17, 80% were currently attending school and 20% had dropped out of school (see Table 1). For those who

[2]PROGRESA offered monthly cash transfers to families living in poverty on condition that they send their school-age children to school. The program changed its name to *Oportunidades* in 2002 and to Prospera in 2015. The scholarship amounts went up as the school-age children reached higher-grade levels. The size of the scholarship under PROGRESA is designed to cover the opportunity cost to the family of keeping their children in school. In 2012, the program served 5.8 million households, with around 24 million people nationwide (almost 1 in 4 Mexicans).

were attending school, the 80% can be divided into 65% who were attending school and not working outside the home, and 15% who were attending school and working outside the home. The 20% who dropped out of school can be divided into 12% who worked outside the home and did not attend school, and 8% who were neither working outside the home nor attending school.[3]

Regarding bullying, the UNESCO (2017) defines it as an "intentional and aggressive behavior occurring repeatedly against a victim where there is a real or perceived power imbalance and where the victims feel vulnerable and powerless to defend themselves." According to Olweus (1994), bullying behaviors can be physical (hitting, kicking, and destruction of property); verbal (teasing, insulting, and threatening); or relational (spreading of rumors and exclusion from a group). According to Griffin and Gross (2004), there are many approaches to measurement of bullying: (1) self-report, (2) peer nomination, (3) teacher report, and (4) direct observation. Regarding self-report, it can be reported directly or by using a test. An example of direct question is used in Rees et al. (2020), where they use the following measure of bullying from the Youth Risk Behavior Surveys (YRBS) in the USA: "During the past 12 months, have you ever been bullied on school prop-

[3]The survey asked these adolescents about their current labor-education situation. The adolescents responded by selecting the group that they were most closely related to, i.e. attending school and not working outside the home, working outside the home and not attending school, working outside the home and attending school; and neither working outside the home nor attending school.

erty?" As to the tests, Griffin and Gross (2004) found three widely tests to measure self-report bullying: (1) the Peer Relations Questionnaire (Rigby, 1998), (2) the Bully/Victim Questionnaire (Olweus, 1997), and (3) the Self-Reported Bullying, Fighting, and Victimization scale (Espelage and Holt, 2001).

In this paper, I use the Peer Relations Questionnaire (PRQ) proposed by Rigby (1998) and adopted for the Mexican context by Palomar (2012). This test includes the following questions regarding bullying: "In the last year that you attended school: (1) other students bothered you (like pulling your hair or throwing objects at you), (2) other students called you bad names, (3) other students left you out of an activity intentionally, (4) other students threatened to hurt you, and (5) you were beaten or kicked".[4] The questions have the following categorical answers: "always", "frequently", "rarely" and "never". I aggregate those answers into scales using principal component analysis, retaining only the first latent factor. Table 10 presents the results of the principal component analysis. Column 1 presents the eigenvalue of the first factor[5], Column 2 presents the questions, and Column 3 shows the loading associated with each question. I then standardized the value of the latent variable to have a mean of zero and a standard deviation of one. The results show that, on average, boys experience higher levels of bullying than girls

[4]Studies utilizing the PRQ include Peterson and Rigby (1999), Pellegrini and Long (2002), and Salmivalli and Nieminen (2002).

[5]The values of the rest of eigenvalues are less than one and, as a consequence, they were not included.

(see Table 1).

Table 1 also presents information regarding other variables that will be used as controls: age, pregnancy, sexual abuse, number of siblings, half-siblings, death of the father, death of the mother, abandonment by the father, abandonment by the mother, parents' use of drugs, parents in prison, change of work by parents, violence within the household, and having social support. I also include the following individual-level education variables: suspended temporarily from school, and repeated at least one academic year. I lack the information regarding test scores, yet I include a test that measures students' cognitive ability (Raven test).[6] In addition, I include a dummy variable that indicates if students have changed school. This can be an important omitted variable since it is possible that some students that suffer from bullying change school and it affects the likelihood of dropping out of school. I also include information regarding junior high schools at the municipality level. This information was obtained from the Information System and Educational Management from the Ministry of Education. The variables included are: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students.

[6]The Raven test is designed to measure non-verbal, abstract, and cognitive functioning. It includes a matrix of geometric designs with one piece missing. The interviewed choose one diagram from a set of eight answers. The Raven test used in this survey has 12 questions and it was adopted to the Mexican case by Palomar (2012).

Table 1 also presents information on macroeconomic factors, natural disasters, and criminal activity that can also affect dropping out of school. The data used to measure natural disasters came from the National Center for the Prevention of Disasters (CENAPRED). In particular, I use a database collected by the Mexican government at the municipal level for all earthquakes and hurricanes that have affected the country in the year prior to the survey. The data on GDP per capita for agricultural, industrial, and service sectors at the state level were taken from Mexico's National Institute of Statistics and Geography (INEGI). Finally, I include information regarding homicides per 100,000 inhabitants at the municipality level in the year prior to the survey. The information regarding homicides came from the vital statistics provided by the National Institute of Statistics and Geography (INEGI).

Table 1 column 4 presents results regarding significant statistical differences between girls and boys in relation to the outcome of interest (dropping out), the variable of interest (bullying), and the control variables. There is no statistically significant difference between girls and boys regarding dropping out of school.[7]

[7]Behrman et al. (2005) found that girls presented higher rates of dropping out of school than boys. In particular, they found that 30% of girls drop out at the age of 13 while this percentage was 15% in the case of boys. To close this gap, the program gave a greater monetary transfer in scholarships to girls in relation to that granted to boys. Schultz (2004) focuses on school enrollment and finds that at the junior high level, the effect on girls was between 7 and 9 percentage points and for boys it was between 5 and 6 percentage points. In addition, Behrman et al. (2005) found differences by gender when analyzing dropping out of school. In particular, they found that for girls the program is more effective in reducing the dropping-out behavior

The results confirm that boys suffer more bullying than girls and that this difference is statistically significant. In relation to the control variables, no statistically significant differences were found. Some exceptions are: social support (girls ask for more social support than boys), suspended from the school (boys are suspended more frequently than girls), and repeated an academic year (boys repeated more than girls).

Finally, Table 1 presents information regarding variables that can be mechanisms through which bullying affects dropping out of school: self-esteem, stress, and anxiety. These variables were constructed using principal component analysis[8]. The self-esteem index is based on Rosenberg (1965). The measure of stress is based on Fliege et al. (2005). Finally, the anxiety scale is based on Achenbach and Rescorla (2001).

3.2 Identification Strategy

This paper analyzes the effects of bullying on the probability of dropping out of school for adolescents participating in PROGRESA. The model to estimate is

during the first year of secondary school and has little impact on dropping-out in the second and third year of secondary school. For boys, they found that the program has a greater impact on reducing dropping-out rates in the second and third year of secondary school. The combination of these results may be reflecting that no differences are observed between boys and girls regarding dropping out of school.

[8]Table 10 presents the principal components results.

given by:

$$Y_{im} = \beta_0 + \beta_1 \, T_{im} + X_{im}\gamma_1 + Z_m\gamma_2 + \alpha_m + \epsilon_{im} \tag{1}$$

Where Y_{im} is the outcome of interest (a dummy variable indicating whether an adolescent i has dropped out of school at the municipality m), T_{im} is the variable of interest (bullying), X_{im} is a vector of observed control variables for the individual i at the municipality m, Z_m is a vector of observed control variables at the municipality m, α_m control for fixed effects at the municipality level, and ϵ_{im} is an error term with mean zero. Standard errors are clustered at the municipality level. The coefficient of interest is β_1, which represents the effect of bullying on the likelihood of dropping out of school.

A study of this type presents several econometric challenges. First, the measure of bullying is a proxy variable, so there is a potential problem of a measurement error. It is well-known that when regressors are measured with a random error, the parameters estimated tend to be biased towards zero. Second, bullying may be correlated with other psychological variables not present in the data. If such variables are correlated with the outcome of interest, then they are in the error term ϵ and their correlation with T will generate bias in the estimated impacts of bullying. Finally, although reverse causality is likely to be minimal, it can be a potential problem. A problem of reverse causality can occur if these dropouts return to school and doing so affects the level of bullying. However, using data from Mexico, Baron et al. (2016) find that, once young people between 15 and 18 years old leave school, they are very unlikely to return; this minimizes the possibility that not attending school can affect the level of bullying.

To address the problem of omitted variable bias, I use a recently developed bounding methodology developed by Oster (2017) and an instrumental variable approach proposed by Lewbel (2012). Consider first Oster's methodology. Altonji et. al. (2005) observed that a common approach to evaluate robustness to omitted variable bias is to include additional control variables on the right-hand side of the regression. If such additions do not affect the coefficient of interest, then this coefficient can be considered unlikely to be biased. This strategy implicitly assumes that using information from observed covariates is informative about unobserved variables. Oster formalizes this idea and provides conditions for bounds and identification. If the bounds exclude zero, then the results from the regression can be considered to be robust to the omitted variable bias (see Appendix A).

The second methodology that I will use to check the robustness of the results is an instrumental variable approach. Lewbel (2012) suggests an instrumental variable called identification through heteroscedasticity. In particular, he proposes to exploit the correlation between exogenous variables and heteroscedasticity of model disturbances to achieve identification without imposing any exclusion restrictions. Following Lewbel, I first estimate the following model:

$$T_{im} = \theta_1 + \theta_2 X + \xi_{im} \tag{2}$$

Where the variable T_{im} represents the potential endogenous variable (bullying). X represents all observed control variables in equation (1) and ξ_{im} is the error term. The heteroscedasticity-based identification strategy assumes the existence of heteroscedasticity in ξ (and, as a consequence, in T). In particular, it is assumed that: $cov(X,\xi^2) \neq 0$. Lewbel suggest using $[X - E(X)]\hat{\xi}$ as an instrument for T in estimating (1). Where $\hat{\xi}$ is the predicted residuals obtained by estimating equation (2). Finally, Lewbel points out that the condition $cov(X,\xi^2) \neq 0$ needs to hold only for a subset of the vector X. More detailed explanations can be found in Lewbel (2012).

4 Results

4.1 Bullying and Dropping Out of School

To analyze the effects of bullying on dropping out of school, I first present the results using an OLS regression, and then I apply the bounding and instrumental variable strategies.

Table 2 column 1, presents a linear probability model (OLS regression) of the impact of bullying on the probability of dropping out of school. The only controls that I include are fixed effects at the municipality level. The results show that a one-standard-deviation increase in being bullied raises the probability of dropping out of school by 5.1 percentage points. Column 2 includes the following socio-economic variables: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father's death, mother's dead, abandonment by the father or the mother, parent's use of drugs, parents in prison, parent's change of work, violence within the house, having social support, and fixed effects at the municipality level. A small decrease in the coefficient associated with bullying (0.045) is observed, but it remains statistically significant.

School-level factors and individual-level education variables can also influence dropping out of school. Using data from the United States, Lee and Burkam

(2003)find evidence that school organization and structure influence dropping out of school. Also, the type of school attended appears to matter for dropping out of school. Using data for the state of Guanajuato in Mexico, Tapia García et al. (2010) found that the dropping-out rate was bigger for students attending technical schools: 11.3% vs 10.2% at the state level. In addition, they found that the drop out rates were bigger for boys (11.3%) than for girls (6.6.%). Yet, in both cases, the rates were bigger when comparing with the state drop out rates by gender. In addition, there is evidence that individual-level education factors are important regarding the dropping out of school. Fetler (1989), using data from the USA, find a negative association between academic performance and dropping out. Roderick (1994), analyzing data for urban schools in the USA, finds evidence that repeated grades were associated with dropping out of school. Likewise, Skiba et al. (2014), using data from the USA, find that schools characterized by a high suspension rate also have higher dropout rates.

Table 2 column 3 includes the following individual-level education variables: suspended temporarily from school, repeated at least one academic year, a cognitive test (Raven), and a dummy variable that indicates if the students changed school in the last academic year. I also include the following variables at the municipality level for junior high schools: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Bullying continues to be statistically significant, although the impact is slightly diminished. In particular, one standard deviation increase in being bullied raises the probability of dropping out of school by 4.1 percentage points.

Macroeconomic factors can also affect dropping out of school. Bentaouet-Kattan and Székely (2015), using data from 18 countries in Latin America, found evidence that youth dropping out of school was related to macroeconomic environment and labor market opportunities. Knaul (2002) finds that entering the labor market at an early age has lower returns for women than for men and this can potentially affect school dropout decisions. Natural disasters can also affect the rates of dropping out from school. Takasaki (2012), using data from Fiji, finds that boy's school enrollment is significantly lower than the girls' one among cyclone victims. Finally, another relevant variable for the Mexican context is related to the Drug on Wars declared by President Calderon in 2006. For example, Brown and Velásquez (2017) find that young adults exposed to increased local violence measured by homicides attained significantly fewer years of education, were less likely to complete compulsory schooling, and were more likely to be employed. Table 2 column 4 includes the following variables: a natural logarithm of the gross domestic product of the agricultural, industrial, and service sectors. In addition, I include natural disasters (hurricanes and earthquakes) and homicides per 100,000 inhabitants at the municipality level in the year prior to the survey. After controlling for these variables, the coefficient associated with bullying remains statistically significant (0.041).

Given that bullying is measured with error, if this measurement error is random, then the estimates in Table 2 underestimate the causal effect and, thus, are lower bounds of bullying on dropping out of school. However, the estimates of the impact of bullying are also possibly affected by omitted variable bias. One way to assess this problem is to add controls and to analyze the stability of the parameter of interest. Yet, Oster (2017) shows that just adding controls, which is a common strategy, is not enough to avoid omitted variable bias. Table 3 presents results using Oster's methodology to analyze the robustness of the results in Table 2. First, I present the results under the assumption that $0 \leq \delta \leq 1$, i.e. assuming the relationship between the variable of interest and the (aggregated) controls has the same sign as the relationship between the variable of interest and the (aggregated) unobservables. Column 1 estimates bounds using the value of the R_{max} proposed by Oster (2017), which yields a tight bounds estimate of [0.034, 0.041]. I also present the results when $-1 \leq \delta \leq 0$.[9] Using the R_{max} proposed by Oster,

[9]The case $-1 \leq \delta \leq 0$ assumes that the relationship between T and X_1 has a different sign

the bounding estimated is: [0.041, 0.048]. Finally, I estimate the value of δ that would be needed to derive the coefficient of interest to zero. I find that $\delta = 3.73$. This implies that unobservables have to be 3.73 times as important as control variables in order to drive the coefficient associated to bullying to zero. Since this value is greater than 1, the effect can be considered robust to unobserved variables.

Table 4 presents the results using an instrumental variable constructed through heteroscedasticity following Lewbel (2012). Using this strategy, the results observed using fixed effects and a bounding methodology are maintained.[10] In particular, a small increase is observed in the coefficient associated with bullying (0.045) and it is statistically significant.

4.2 Heterogenous effects

In this section, I analyze heterogeneous effects by sex, age, pregnancy, and death of the father. It is necessary to mention that for these regressions, I use a dummy variable for age. It equals 1 for ages 13 and 14, and it equals zero for ages 15, 16, and 17. Table 5 presents heterogeneous results by sex (column 1),

than the relationship between T and X_2.

[10] I estimate the first-stage regression in equation (2) and test for heteroscedasticity using a Breush-Pagan test. According to the test results (chi^2 = 373, p-value=0.00) there is strong evidence for heteroscedasticity in the first stage regression.

age (column 2), pregnancy (column 3), and death of the father (column 4). I find evidence of important heterogeneous effects by sex. In particular, I find that bullying affects only girls' probability of dropping out of school, but not that of boys'. This result appears to support the "gender paradox effect" hypothesis proposed by Loeber and Keenan (1994), which establishes that boys experience higher rates of bullying than girls, but that bullying affects more negatively the well-being of girls as compared to boys. Regarding age, the results show that bullying has more negative consequences for young people between 15 and 17 years old than for those between 13 and 14 years old. Finally, there is no evidence of heterogeneous effects based on pregnancy or death of the father.

4.3 Mechanisms

Bullying is an important factor explaining the probability of dropping out of school, particularly for girls. However, this opens the question about what the mechanisms by which bullying affects the dropout rates are. In particular, is bullying increasing the dropout rates because of its effects on adolescents' well-being (self-esteem, anxiety, and stress)? Or is bullying raising the probability of dropping out of school *independent* of the problems associated with adolescents' well-being ?

Table 6 presents the results when self-esteem (column 1), stress (column 2), and anxiety (column 3) are considered as a mechanism between bullying and dropping out of school. After including these variables, the coefficient associated with bullying remains almost stable. So, there appears to be a strong direct effect of bullying on dropouts. Another interpretation of this result is that mechanisms other than those used above have an indirect effect on dropout rates.

4.4 Robustness checks

4.4.1 Alternative measure of bullying

To generate the measure of bullying, I use principal component analysis. To check that the results presented were not a consequence of this methodology, I use an alternative measure. In particular, I add the values of each of the questions related to bullying and I generate a new bullying index. This strategy assumes that all the questions have the same weight. Finally, I standardize this measure so that it has a mean of zero and a standard deviation equal to one. Table 7 replicates the results of Table 2. It is observed that the coefficient associated with bullying remains statistically significant and with a slightly greater magnitude (0.042) in relation to the strategy using principal component analysis (0.041).

4.4.2 Functional form

Chatla and Shmueli (2013) pointed out some problems when using ordinary least squares (OLS) to estimate a model with a binary dependent variable: (1) the homoscedasticity assumption is violated; (2) the values are not necessarily constrained to 0 and 1; and (3) the functional forms are not necessarily linear. Yet, there are ways to address each concern. Regarding homoscedasticity, Angrist and Pischke (2009) suggest using heteroskedasticity-consistent robust standard errors estimates. Regarding the problem of constrained values between 0 and 1, this represents a problem when our focus is on prediction. Yet, Friedman (2009) suggest that "the violations themselves do not guarantee that this approach will not work." In particular, they point out that, when the probabilities are used for classification, we are only interested in comparing the probability of occurrence P(Y=1) and no occurrence P(Y=0) and classifying the respective observation to the class with the higher probability. Finally, regarding the challenge of the functional form, it is possible that the functional form is nonlinear and it generates bias on the estimators. As an alternative to this concern, Gordon (1994) suggest using logit or probit functions. Yet, Angrist and Pischke (2009) suggest that: "The LPM won't give the true marginal effects from the right nonlinear model. But then, the same is true for the wrong nonlinear model! The fact that we have a probit, a logit, and the LPM is just a statement to the fact that we don't know what the "right" model is. Hence, there is a lot to be said for sticking to a linear regression function as compared to a fairly arbitrary choice of a non-linear one!"

To test for how robust the results regarding the functional form are, Table 8 presents results using OLS, probit, and logit models. The OLS standard errors are presented using heteroskedasticity-consistent robust standard errors. The results show that regardless of the functional form, there is a statistically significant effect of bullying on dropping out of the school. In particular, a one standard deviation increase in being bullied raises the probability of dropping out of school by 4.1 percentage points when using OLS, by 3.6 percentage points when using a logit model, and by 3.5 pp when using a probit model.

4.4.3 Heterogeneous Effects by Sex

The results show that bullying affects only girls' probability of dropping out of school, but not that of boys'. Yet, this result can be biased as a consequence of omitted variables. Table 9 column 1 presents results using Oster's methodology to analyze the robustness of this result. Assuming that $-1 \leq \delta \leq 1$ and the R_{max} proposed by Oster (2017) yields a bounds estimate of [0.034, 0.069]. Then, I present the results using Lewbel's instrumental variables strategy. The coefficient associated with bullying is statistically significant (0.066).[11] Thus, both methodologies suggest that the result is robust to the omitted variable bias.

5 Conclusion

This paper finds evidence that bullying leads to increased drop out rates in adolescents participating in the Mexican conditional cash transfer program PROGRESA, especially among girls. The previous literature that has analyzed this relationship has faced the problem of the omitted variable bias. To address this problem, I use two new methodologies: a bounding approach developed by Oster (2017) and an instrumental variable strategy proposed by Lewbel (2012). The bounding and instrumental variable strategies suggest that the result is robust to the omitted variable bias.

This result supports the "gender paradox effect" of bullying proposed by Loeber and Keenan (1994). This paradox states that boys experience higher rates of bullying than girls, but that bullying has more negative consequences on the well-being of girls than on boys' well-being. Regarding the mechanisms, I analyze

[11]I estimate the first-stage regression in equation (2) and test for heteroscedasticity using a Breush-Pagan test. According to the test results (chi^2 = 113, p-value=0.00). There is strong evidence for heteroscedasticity in the first stage regression.

whether bullying affects girls' probability of dropping out of school through self-esteem, anxiety, and stress. However, I fail to find strong evidence that self-esteem, anxiety, and stress are the mechanisms.

PROGRESA was a successful conditional cash transfer program that increased the enrollment of adolescents living in poverty. Unfortunately, the condition of poverty has been associated with increasing rates of being bullied. Thus, on the one hand, PROGRESA reduces the cost of attending school for these adolescents; but, on the other hand, bullying increases the chances that these adolescents drop out of school. While the results of this paper apply to the case of PROGRESA, it would be very useful to explore whether this situation is happening in other conditional cash transfers programs around the world.

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6 Tables

Table 1: Descriptive Statistics

	Total	Girls	Boys	P-value
Dropping out: 1 Yes 0 No	0.20	0.20	0.20	0.91
Bullying (Std)	0.00	-0.18	0.14	0.00***
Age	14.92	14.91	14.92	0.95
Pregnancy: 1 Yes 0 No	0.05	0.06	0.04	0.31
Sexual abuse: 1 Yes 0 No	0.01	0.01	0.01	0.49
Siblings	2.67	2.62	2.71	0.35
Half-siblings	0.20	0.21	0.18	0.30
Father death	0.04	0.05	0.03	0.28
Mother death	0.01	0.01	0.02	0.29
Abandonment by the father	0.07	0.08	0.06	0.42
Abandonment by the mother	0.03	0.03	0.02	0.31
Drug use (parents)	0.02	0.01	0.02	0.06*
Prison (parents)	0.04	0.05	0.04	0.92
Change of work (parents): 1 Yes 0 No	0.11	0.12	0.10	0.34
Violence inside your house: 1 Yes 0 No	0.04	0.05	0.03	0.06*
Social support (Std)	0.00	0.16	-0.12	0.00***
Suspended: 1 Yes 0 No	0.13	0.08	0.17	0.00***
Repeated a grade: 1 Yes 0 No	0.26	0.20	0.31	0.00***
Change of school: 1 Yes 0 No	0.08	0.09	0.07	0.44
Raven test	6.57	6.41	6.70	0.07*
Technical junior high schools (%)	11.64	11.48	11.76	0.57
Private junior high schools (%)	13.37	12.66	13.94	0.17
Female students in junior high schools (%)	49.89	49.91	49.88	0.80
Female teachers in junior high schools (%)	55.18	55.47	54.95	0.30
Students per classroom in junior high schools	26.01	25.77	26.20	0.22
Natural disasters: 1 Yes 0 No	0.11	0.12	0.11	0.62
Homicides per 100,000 inhabitants	20.95	20.70	21.15	0.84
Log (Agriculture GDP Per Capita)	8.39	8.35	8.43	0.13
Log (Industry GDP Per Capita)	10.34	10.33	10.35	0.58
Log (Services GDP Per Capita)	11.07	11.07	11.08	0.57
Self-esteem (Std)	0.00	0.00	0.00	0.99
Stress (Std)	0.00	-0.02	0.02	0.51
Anxiety (Std)	0.00	0.14	-0.11	0.00***

Source: Survey of Resilience and Social Mobility (Progresa-Oportunidades Program). The data regarding junior high schools were obtained from the Information System and Educational Management. The information regarding natural disasters was obtained from the National Center for the Prevention of Disasters (CENAPRED), and the data regarding GDP from the National Institute of Statistics and Geography (INEGI).

Table 2: OLS Estimates: Effects of Bullying on Dropping Out of School

	(1)	(2)	(3)	(4)
Dependent variable: Dropping Out				
Bullying (Std)	0.051***	0.045***	0.041**	0.041**
	(0.016)	(0.017)	(0.017)	(0.017)
Sex (Female=1)		-0.002	-0.000	-0.000
		(0.020)	(0.021)	(0.021)
Age		0.065***	0.069***	0.069***
		(0.010)	(0.010)	(0.010)
Pregnancy: 1 Yes 0 No		0.132**	0.128**	0.128**
		(0.058)	(0.057)	(0.057)
Sexual abuse: 1 Yes 0 No		-0.156	-0.182*	-0.182*
		(0.095)	(0.097)	(0.097)
Siblings		0.027***	0.025***	0.025***
		(0.008)	(0.008)	(0.008)
Half-siblings		-0.026	-0.028	-0.028
		(0.029)	(0.027)	(0.027)
Father death		0.186**	0.179**	0.179**
		(0.086)	(0.084)	(0.084)
Mother death		0.239*	0.262**	0.262**
		(0.140)	(0.128)	(0.128)
Abandonment by the father		0.085**	0.084**	0.084**
		(0.040)	(0.040)	(0.040)
Abandonment by the mother		-0.017	-0.006	-0.006
		(0.081)	(0.081)	(0.081)
Drug use (parents)		-0.082	-0.049	-0.049
		(0.073)	(0.077)	(0.077)
Prison (parents)		0.035	0.043	0.043
		(0.056)	(0.056)	(0.056)
Change of work (parents): 1 Yes 0 No		-0.038	-0.030	-0.030
		(0.034)	(0.034)	(0.034)
Violence inside your house: 1 Yes 0 No		-0.016	-0.014	-0.014
		(0.061)	(0.062)	(0.062)
Social support		-0.028**	-0.025*	-0.025*
		(0.013)	(0.013)	(0.013)
Suspended: 1 Yes 0 No			0.082**	0.082**
			(0.040)	(0.040)
Repeated a grade: 1 Yes 0 No			-0.031	-0.031
			(0.025)	(0.025)
Change of school: 1 Yes 0 No			-0.105**	-0.105**
			(0.041)	(0.041)
Raven test			-0.011**	-0.011**
			(0.005)	(0.005)
Students per classroom in junior high schools			0.006***	0.006**
			(0.002)	(0.003)
Technical junior high schools (%)			0.004	-0.032***
			(0.002)	(0.005)
Private junior high schools (%)			0.000	-0.010***
			(0.000)	(0.003)
Female teachers in junior high schools (%)			0.006*	0.011**
			(0.003)	(0.005)
Female students in junior high schools (%)			-0.084***	0.282***
			(0.011)	(0.055)
Natural disasters: 1 Yes 0 No				2.033***
				(0.357)
Homicides per 100,000 inhabitants				-0.015***
				(0.003)
Log (Agriculture GDP Per Capita)				0.014
				(0.012)
Log (Industry GDP Per Capita)				-0.636***
				(0.112)
Log (Services GDP Per Capita)				2.310***
				(0.441)
Municipality FE	Yes	Yes	Yes	Yes
R^2	0.12	0.21	0.22	0.22
Observations	1039	1038	1038	1038

Note: Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Bounding Methodology

	Oster ($R_{max} = 1.3\tilde{R}$)	δ for ($\beta = 0$)
Bullying ($0 \leq \delta \leq 1$):	[0.034, 0.041]	3.73
Bullying ($-1 \leq \delta \leq 0$):	[0.041, 0.048]	3.73
Controls	Yes	Yes
Municipality FE	Yes	Yes

Note: Interval in squares brackets are the bounds. The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 4: Lewbel's Instrumental Variables

	(1)
Bullying (Std):	.045**
	(.018)
Controls	Yes
Municipality FE	Yes
R^2	0.22
Observations	1,038
F-statistic first stage	95.47

The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors. Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Heterogeneous Effects with Respect to Sex, Age, Pregnancy, and Father Death

	(1)	(2)	(3)	(4)
Dependent variable: Dropping Out				
Bullying (Std)	0.025	0.065***	0.043**	0.042**
	(0.017)	(0.022)	(0.017)	(0.017)
Bullying*Sex	0.055**			
	(0.026)			
Bullying*Age		-0.050*		
		(0.026)		
Bullying*Pregnancy			-0.060	
			(0.070)	
Bullying*Father death				-0.007
				(0.054)
Controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
R^2	0.23	0.23	0.22	0.22
Observations	1038	1038	1038	1038

Note: Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 6: Mechanisms: Effects of Bullying on Whether Adolescents Dropped Out of School

	(1)	(2)	(3)
Dependent variable: Dropping Out			
Bullying (Std)	0.041**	0.042**	0.041**
	(0.017)	(0.017)	(0.018)
Self-esteem (Std)	-0.014		
	(0.013)		
Stress (Std)		-0.004	
		(0.012)	
Anxiety (Std)			0.001
			(0.014)
Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
R^2	0.22	0.22	0.22
Observations	1037	1038	1038

Note: Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 7: Robustness Check 1: Alternative Measure of Bullying

	(1)	(2)	(3)	(4)
Dependent variable: Dropping Out				
Bullying	0.051***	0.045***	0.042**	0.042**
	(0.016)	(0.017)	(0.017)	(0.017)
Individual Controls	No	Yes	Yes	Yes
School Controls	No	No	Yes	Yes
Macroeconomic Controls	No	No	No	Yes
Municipality FE	Yes	Yes	Yes	Yes
R^2	0.12	0.21	0.22	0.22
Observations	1039	1038	1038	1038

Note: Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The individual control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. The school control variables are: suspended, repeated a grade, change of school, and Raven test. In addition, information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, the macroeconomic control variables are: information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 8: Robustness Check 2: Functional Form

	OLS	Logit	Probit
Dependent variable: Dropping Out			
Bullying (Std)	0.041**	0.338***	0.185***
	(0.016)	(0.102)	(0.060)
Controls	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes

Note: Clustered standard errors displayed in parenthesis at the municipality level for logit and probit.The OLS standard errors are presented using heteroskedasticity-consistent robust standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 9: Robustness Check 3: Bounding Methodology and Lewbel's Instrumental Variables for Gender

	Oster ($R_{max} = 1.3\tilde{R}$) ($-1 \leq \delta \leq 1$)	Lewbel's IV
Bullying*Sex :	[0.034, 0.069]	.066**
		(.027)
Controls	Yes	Yes
Municipality FE	Yes	Yes

Note: Interval in squares brackets are the bounds. Clustered standard errors displayed in parenthesis at the municipality level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ The control variables are: sex, age, pregnancy, sexual abuse, siblings, half-siblings, father death, mother death, abandonment by father, abandonment by mother, drugs use (parents), parents in prison, change of work, violence inside the house, and having social support. In addition, it includes the following individual-level education variables: suspended, repeated a grade, change of school, and Raven test. Information regarding junior high schools at the municipality level: students per classroom, percentage of technical schools, percentage of private schools, percentage of female teachers, and percentage of female students. Finally, I include information regarding natural disasters, homicides per 100,000 inhabitants, and GDP per capita for the agricultural, industrial, and service sectors.

Table 10: Latent variable scales

Scale Name	Survey Question	Factor Loading
Bullying	[1] Other students bother me (pulling hair, throwing objects, etc.)	0.3948
Eigenvalue: 2.9	[2] Other students called me bad names	0.4499
	[3] Other students left me out of an activity intentionally	0.4596
	[4] Other students threatened to hurt me	0.4686
	[5] I was beaten or kicked	0.4592
Self-esteem	[1] I am satisfied with myself	0.3678
Eigenvalue: 2.1	[2] I am able to do things as well as others	0.4358
	[3] I am a worthy person	0.4845
	[4] I have good qualities	0.4720
	[5] I have a positive attitude toward myself	0.4661
Stress	[1] I realize that I get into conflict situations	0.1523
Eigenvalue: 4.6	[2] I feel overwhelmed with responsibilities	0.2282
	[3] I feel mentally tired	0.2917
	[4] I feel physically tired	0.2900
	[5] I'm feeling down	0.3237
	[6] I feel frustrated	0.3251
	[7] I feel pressured by other people	0.3087
	[8] I feel tense	0.3213
	[9] My problems seem to be accumulating	0.3130
	[10] I feel like I'm doing things because I should, not because I want to	0.2362
	[11] I'm afraid I can not achieve my goals	0.2689
	[12] I have to make many decisions	0.2014
	[13] I have difficulty to relax	0.2826
Anxiety	[1] I cry a lot	0.2904
Eigenvalue: 3.7	[2] I'm afraid of some animals, situations or places	0.2273
	[3] I'm afraid to go to school	0.2414
	[4] I'm afraid to do something bad	0.1661
	[5] I feel like I have to be perfect	0.1746
	[6] I feel like nobody loves me	0.3359
	[7] I feel inferior to others	0.3307
	[8] I'm nervous or tense	0.3048
	[9] I am very fearful or anxious	0.3064
	[10] I feel very guilty	0.3318
	[11] I get bored or easily embarrassed	0.2933
	[12] I think about killing myself	0.2686
	[13] I worry a lot	0.2653

7 Appendix A

Following the notation in Oster, the full model has the form:

Y= β T + X_1 + X_2 +ϵ.

where T is the variable of interest, X_1 contains the *observed* control variables multiplied by their coefficients, i.e. $X_1 = \sum_{j=1}^{J_o} X_j^o \gamma_j^o$, and X_2 contains all *unobserved* variables multiplied by their coefficients, i.e. $X_2 = \sum_{j=1}^{J_u} X_j^u \gamma_j^u$. Finally, ϵ is a random error that represents measurement error in Y and is uncorrelated with X_1, X_2, and T. Oster suggests the following approach to account for omitted variable bias:

(1) Regress Y on T, and report the parameter on T, denoted by β^0, and the R-squared coefficient, denoted by R^0.

(2) Regress Y on T and X_1, and report the parameter on T, denoted by $\tilde{\beta}$, and the R-squared coefficient, denoted by $\tilde{R}$.

(3) Define R_{max} as the overall R-squared of the model, that is the R-squared that would be obtained from a regression of Y on both, observables (T, X_1) and

unobservables (X_2).

Also, define δ to be a parameter that ensures the equality $\frac{Cov(T,X_2)}{Var(X_2)} = \delta\frac{Cov(T,X_1)}{Var(X_1)}$. In other words, this relationship formalizes the idea of Altonji et al. (2005) that the magnitude and sign of the relationship between T and X_1 provides some information about the magnitude and sign of the relationship between T and X_2. For example, if $-1 \leq \delta \leq 1$, then the variable of interest (T) is no more correlated with unobservables (X_2) than it is correlated with observables (X_1). The case $0 \leq \delta \leq 1$ has a similar interpretation, with the additional assumption that the relationship between T and X_1 have the same sign as the relationship between T and X_2.

Oster shows that $\beta^* \approx \tilde{\beta} - \delta\frac{\left(\beta^0-\tilde{\beta}\right)\left(R_{max}-\tilde{R}\right)}{\left(\tilde{R}-R^0\right)}$ is a consistent estimator of the effect of T on Y, β. Notice that this is a close approximation to the consistent estimator and it is used to present some intuition regarding the methodology. The complete approximation is presented in Oster (2017).

In order to estimate β^*, one needs estimates of δ and R_{max}. Oster proposes assumptions for δ and R_{max} that allows one to determine whether β^* is different from zero. Oster proposes that $R_{max} = min\{1.3\tilde{R}, 1\}$, where the $\tilde{R}$ is defined above.

The cut-off value of 1.3 is derived from a sample of papers that have used randomized controlled trials and nonrandomized data and published in the *American Economic Review*, *Quarterly Journal of Economics*, *The Journal of Political Economy*, and *Econometrica* from 2008-2010. She determined that using this cut-off allowed 90% of the randomized and 50% of the nonrandomized results to continue being statistically significant. After determining the value of R_{max}, Oster suggests that β^* be calculated for all the following ranges of δ: $0 \leq \delta \leq 1$. In addition, I will present the results for δ: $-1 \leq \delta \leq 0$. This allows one to construct the set $[\tilde{\beta},\ \beta^*]$. If this set excludes zero, the results from the controlled regressions can be considered to be robust to omitted variable bias. In other words, the results indicate that $\beta^* \neq 0$.

Another approach is to calculate the value of δ that would be needed to derive the coefficient of interest to zero. For example, if $\delta = 2$, it indicates that to generate a zero treatment effect, unobservables should be twice as important as observables. Oster (2017) suggest that $\delta = 1$ would be an appropriate cut-off, i.e. unorbservables variables explain as much of the outcome as the actual controls.