Three Essays on Development Economics

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Dedication

To my parents, Blanca and Adan. Gracias por todo su amor.

Abstract

This dissertation consists of three empirical essays on development economics. The first essay estimates the effect of bullying on dropping out of school. I find that boys experience higher rates of bullying than girls, but bullying affects only girls' probability of dropping out of school. The second essay investigates the accuracy of information regarding assets collected through household surveys. Using a survey that asks questions regarding household assets to the wife and to the husband from families participating in the Mexican conditional cash transfer program PROGRESA, I find discrepancies between the spouses in the possession of assets reported. The third essay analyzes the use of disaster funds (government saving resources ex-ante for post-disaster use) to protect families consumption from a natural disaster. Using data for Hurricane Earl in Puebla, Mexico, where a disaster fund was implemented; results show a decrease in consumption, including beans, which is an essential staple good for Mexican families.

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Chapter 1

Introduction

This dissertation consists of three empirical essays on development economics. The first essay (Chapter 2), "Girls vs. Boys: Who is Dropping Out of School Because of Bullying?", estimates the effect of bullying on dropping out of school. Despite the rising interest in bullying, there is little evidence about its effects on dropout rates. Furthermore, the limited evidence suffers from serious problems of omitted variable bias. A random experiment is impossible to conduct and the literature has found problems to identify an instrumental variable. To address the problem of omitted variable bias, I implement two novel bounding econometric techniques: one proposed by Oster (2016) and the other by Krauth (2016). By using these methodologies and data from adolescents participating in the Mexican conditional cash transfer program PROGRESA, I find that boys experience higher rates of bullying than girls, but bullying affects only girls' probability of dropping out of school.

The second essay (Chapter 3), "What Can Self-Esteem and Self-Control Tell us about Problems in Survey Data?", investigates the accuracy of information on assets collected through household surveys. Household assets information is frequently used to do empirical research, and to guide public policy, such as generating official measures of poverty or deciding who participates in social programs. Using a survey that asks questions regarding household assets to the wife and to the husband from families participating in the Mexican conditional cash transfer program PROGRESA, I find discrepancies between spouses in the possession of assets reported. For example, when asked about the possession of a washing machine, the information reported by the spouses did not coincide in 24% of the households. Psychological evidence has found that individuals with low self-control are more likely to cheat in situations when cheating provides an advantage, and individuals with low self-esteem are more likely to present misleading information in order to influence others' points of view about them. As a consequence, the information collected by household surveys potentially can be affected by the self-esteem and self-control of the individuals who are interviewed. Ordinary Least Squares results show that self-esteem and self-control explain the difference in the possession of assets reported. To address the problem of omitted variable bias, two bounding techniques are implemented: Oster (2016) and Krauth (2016). The results are robust to the problem of omitted variables when Oste's bounding methodology is implemented, but not when Krauth's methodology is implemented.

The third essay (Chapter 4), "Are Disaster Funds Enough to Smooth Consumption?", analyzes the use of disaster funds to protect families' consumption levels from a natural disaster. Natural disasters worldwide have increased considerably as a consequence of climate change, and empirical evidence has found that individuals decrease their levels of consumption following a natural disaster. While countries can rely on loans and aid from the international community when facing a natural disaster, one alternative is to use disaster funds and catastrophe bonds. Mexico was the first developing country to use disaster funds and catastrophe bonds through the Fund for Natural Disasters (FONDEN). The FONDEN program provides food to households and resources for the reconstruction of infrastructure. De Janvry, Del Valle, and Sadoulet (2016) find evidence that this program increases local economic activity between 2 and 4 percent in the year following the disaster. Yet, can FONDEN smooth the consumption of the families affected? To answer this question, I analyze data for Hurricane Earl in Puebla, Mexico, where FONDEN resources were implemented. Using a difference-in-difference strategy, results show a decrease in consumption, including beans, which is an essential staple good for Mexican families. It is possible that the consumption of families would have been more affected without the FONDEN; yet, the resources of FONDEN were not enough to fully smooth families' consumption.

The results of these essays have implications for current public policy. Regarding the first essay, the Sustainable Development Goals (SDGs), adopted by 193 countries, made a commitment that all girls and boys will complete their secondary education by 2030. Yet, my paper suggests that bullying is a roadblock in achieving this goal, particularly for girls. The second essay sends a message regarding the quality of data about assets. For example, when using data to construct a proxy means test, policy makers recognize that individuals have incentives to underreport income. As a consequence, they use variables such as the possession of assets to proxy the real income of the households. It is assumed that there are no incentives to misreport these variables. Yet, this paper presents evidence that contradicts this assumption. In this sense, it is necessary to implement strategies that can provide incentives to individuals to accurately report the data. Finally, the third essay presents evidence that the FONDEN program was not enough to protect the consumption of families who were affected. In this sense, it is necessary that the program review whether the quantity, quality, and periodicity with which food is distributed are the most appropriate. Improving these factors potentially can help to smooth the consumption of families affected in the short term by a natural disaster.

Chapter 2

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

2.1 Introduction

Bullying is a problem that exists in 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 (United Nations, 2014). Alarmingly, bullying has been associated with increasing levels of depression (Tfoti, Farringon, Lösel, and Loeber, 2011), problems of low self-esteem (Smokowski and Kopaz, 2005), and affecting academic performance (Nakamoto and Shwartz, 2010). Despite the overall negatives effects of bullying on the well-being of adolescents, 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 16 years old from families participating in the Mexican conditional cash transfer program PROGRESA. The results show that boys experience higher rates of bullying than girls, but bullying has consequences for dropping out of school only for girls. In particular, one standard deviation increase in being bullied increases the probability of girls dropping out of school by 10 percentage points.

One of the United Nations Sustainable Development Goals (SDGs) states that all girls and boys will complete their secondary education by 2030 (United Nations, 2015). Yet, bullying can be a roadblock in achieving this goal. 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 to cope with an even minimize - bullying, but this information is not completely observed in the data.

An approach to evaluate the robustness of estimated relationships to omitted variable bias is to include additional control variables in a regression. Altonji, et al. (2005) and Oster (2016) observed that adding controls is not enough. In particular, they argue that it is necessary to observe the movements in the coefficient of interest, but also the changes in the R-squared. To assess the problem of omitted variable bias, I use two recently developed bounding methodologies: one developed by Oster (2016) and the other by Krauth (2016). Their strategy assumes that adding observed control variables is informative about the bias due to unobservable variables, and based on this assumption, conditions for bounds and identification are provided.

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

This paper contributes to the literature showing that bullying has important consequences for dropping out of school. Using the methodologies of Oster (2016) and Krauth (2016), 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 effect establishes that boys experience higher rates of bullying than girls, but bullying affects more negatively the well-being of girls than of boys. Finally, using the methodology proposed by Acharia et al. (2016), I examine whether bullying affects girls probability of dropping out of school through three different channels: self-esteem, anxiety, and stress. I find no evidence to suggest that the impact of bullying on dropout rates is due to its effects on self-esteem, anxiety, or stress.

In terms of public policy, it is useful to analyze the relationship between bullying and conditional cash transfers (CCTs). CCTs have ben shown to increase the enrollment of adolescents from low-income families in schools;[2] but the negative social stigma associated with poverty potentially makes these adolescents more vulnerable to being bullied at school. Székely (2015), using a survey of dropouts between 15 and 17 years old in Mexico, finds that the percentage of dropouts who reported harassment by other students as the principal cause for dropping out of school is 2.8%. But this reason is 11.3% for dropouts who have a PROGRESA scholarship. In this sense, bullying potentially can reduce the positive effects of PROGRESA and it will be useful to understand if this result is a consequence of the stigma from being poor

[2]Conditional cash transfers (CCTs) have systematically proved to be effective policies to reduce dropout rates (Kremer et al. 2013, Glewwe and Muralidharan 2016, Snilstveit et al. 2016). These programs offer cash transfers to families living in poverty on the condition that they send their school-age children to school. These programs were started with Mexicos well-known social program PROGRESA, which showed positive impacts on school enrollment. For example, the program resulted in one additional year of school in the adolescents who are beneficiaries (Skoufias and Parker 2001). And based on this evidence, more than 50 countries have implemented CCT programs.

or from participating in the PROGRESA program. While the results presented in this paper are limited to adolescents participating in PROGRESA, this could be an unintended consequence of other conditional cash transfer programs around the world.

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.

2.2 Related Literature

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Székely (2015), using a national survey conducted in Mexico on dropouts between 15 and 17 years old records the following reasons given by dropouts for not attending school (see Table 2.1): lack of money (39%); lack of interest in school (11%); and the student failed some courses (11%). When analyzing the data for adolescents who received scholarships from PROGRESA, he found that lack of money is still one of the most significant reasons, but the percentage is reduced to 24%. More interesting is the question related to dropping out of school as a consequence of harassment by other students. At the national level, the percentage of dropouts who reported this reason is only 2.8%, but this reason is reported by 11.3% of dropouts who previously had a PROGRESA scholarship. This result may simple be a consequence of the poverty of PROGRESA's students. However, it is important to consider whether it can be due to a social stigma associated with participating in this program.

According to INEGI (2014), 32.2% of students in Mexico between 12 and 18 years old were victims of abuse by their classmates. To the best of my knowledge, there are no studies in Mexico about the causal effects of bullying on dropping out of school, yet it is clear that being bullied has negative consequences on the adolescents' well-being. Sarzosa and Urzúa (2015) find that being bullied at school causes depression, stress, and overall dissatisfaction with life. And dissatisfaction with life is associated with low levels of self-estem. In this sense, Waddell (2006) finds that adolescents with low self-esteem complete fewer years of upper secondary school education and are less likely to be employed as adults. These findings suggest that being bullied may be an important factor to explain why young people drop out of school.

It is equally important to consider the adolescents gender when analyzing bullying. Loeber and Keenan (1994) show that boys experience higher rates of bullying than girls, but bullying affects more negatively the well-being of girls than boys (the gender paradox). 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.

To analyze the effect of bullying on dropping out of school, I use data for adolescents participating in the Mexican conditional cash transfer program, PROGRESA. PROGRESA offers monthly cash transfers to families living in poverty on the condition that they send their school-age children to school.[3] The scholarship amounts increase as the school-age children reach 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. This opportunity cost is measured as the potential salary these children could earn from working (Levy and Rodríguez, 2005).

[3]In addition, the adolescents need to participate in local health talk workshops on a regular basis.

Despite the success of PROGRESA,[4] the percentage of lower secondary students who continued onto upper secondary school was below 60% until 2010. From 2011 to 2014, this percentage increased from 64.5% to 71.4%. While this increase is considerable, almost 30% of adolescents still do not reach upper secondary school.[5] Gutiérrez, Norman and Alcalá (2013), find that 35% of adolescents between 14 and 17 years old from families participating in this program are not enrolled in school, and this percentage is higher than the national rate of 27%.

Bentaouet and Székely (2014), using data from Mexico, find that having a post-secondary education is associated with income levels approximately 3.5 times higher than those observed for individuals with only a lower secondary education, and 2 times higher than individuals with an upper secondary education. If the returns on education are high in Mexico and the opportunity cost is covered, one would expect the students in the PROGRESA program to continue attending the school. However, the program design does not consider other potential factors that can increase the cost of attending school, such as bullying.

[4]The evaluations of the program have shown positive impacts. For example, PROGRESA increased years of schooling by one year for adolescents who participated in the program (Skoufias and Parker, 2001), and children between 12 and 36 months who participated in PROGRESA were one centimeter taller (Behrman, et. al. 2008). In 2002, the program changed its name to *Oportunidades*. Based on its success, the program expanded to include five million families (i.e. one in five families in Mexico) and extended the scholarships to upper secondary school students. Also, a new incentive was incorporated called *Jóvenes con Oportunidades*, which gives money directly to the students who complete upper secondary education. Under *Oportunidades*, the program expanded its presence in urban areas. In particular, from 2008 to 2010, the number of participating families in urban areas increased from 759,494 to 1,559,494. In 2015, the program changed its name to PROSPERA, adding new components in order to promote productive activities among the women, such as access to credit at a low interest rate. Today, the program serves more than 6.8 million families in Mexico.

[5]It is possible that this result is consequence of the expansion of the program to urban areas. When the program was predominantly in rural areas, the transition from lower secondary to upper secondary was below 60%. But, when the program incorporated a considerable number of children in urban areas this percentage increased to 71.4%. In other words, this increase in the percentage is potentially capturing the higher rates of enrollment in urban areas rather than successful improvements of the program.

2.3 Data

To analyze the effects of bullying on dropping out of the school, I use a database that was developed in 2010 to analyze the conditions of families living in poverty who were participating in Mexico's PROGRESA conditional cash transfer program. The survey collected information on the non-cognitive skills of adolescents and their parents. A random sample of 2,112 households was selected from families participating in the program in both rural and urban areas. In the case of the adolescents, it was decided to collect information from those between 13 and 16 years old. The survey collected information from 1,093 of these adolescents, who lived in 837 households. Two children who never went to school were excluded, so the final sample for this study is 1,091 adolescents.

Of these 1,091 young people between the ages of 13 and 16, 80.3% were currently attending school and 19.7% had dropped out of school. For those who were attending the school, the 80.3% can be divided into 65.4% who were attending school and not working outside the home, and 14.9% who were attending the school and working outside the home. The 19.7% who dropped out of the school can be divided into 11.5% who were working outside the home and not attending school, and 8.2% who were neither working outside the home nor attending school (see Table 2.2).[6] There are important differences between boys and girls who dropped out of school. Regarding the adolescents who neither work outside the home nor attend school, the percentage of boys (out of all boys) in this group is only 3.3%, while the percentage of girls (out of all girls) is four times higher (14.3%). In the case of the adolescents who were working outside the home and not attending school, the percentage of girls

[6]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.

in this group (out of all girls) is 5.2%, while the percentage of boys (out of all boys) is more than three times higher (16.5%).

I develop an index of bullying based on principal components. In addition, I use this methodology to develop indexes for the following variables that I will use as controls: self-esteem, authoritative parents, and family support. The bullying index is based on Rigby (1998), and the self-esteem index is based on Rosenberg (1965). The measure of authoritative parenting style is based on Arnold, OLeary, Wolff and Acker (1993) and Robinson et al. (1995). Finally, the family support scale is based on Millburn (1987) and Zimet, Dahlem, and Farley (1988). All the tests were adapted by Palomar (2015) in Mexico. The questions have the following categorical answers: "always, "frequently, "rarely and "never. I aggregate those answers into scales using principal components analysis, retaining only the first latent factor.[7] I then standardized the value of the latent variables to have a mean of zero and a standard deviation of one. The results show that there is little difference between boys and girls regarding self-esteem, authoritative parents, and family support. However, on average, boys experience higher levels of bullying than girls (see Table 2.3).

The data in Table 2.3 also contain other information that I will use as control variables. Regarding health problems, 5.1% of the adolescents have (or have had) a disease that interferes (interfered) with their activities. This percentage is higher for girls (6.6%) than for boys (3.9%). There are 4.4% children who have a parent in prison, and 5.4% of children for whom one parent has died. The data also contain information on whether girls have become pregnant and whether boys have impregnated girls. Overall, 4.8% of these adolescents stated they are in this situation. This

[7]I present the results of the principal components analysis in Table A1 of the appendix. Column 1 presents the scales with its eigenvalues, Column 2 presents the questions used to build each scale, and Column 3 shows the loading associated with each question.

percentage is 5.5% for girls and 4.2% for boys. Concerning siblings, on average, these adolescents have three siblings, of which two are older. Table 2.3 also reports information about alcohol consumption of parents. The adolescents reported that 2.3% of their mothers consume alcohol, while the percentage is 24.6% for fathers. Regarding insecurity, these adolescents were asked questions about observing the following activities in their neighborhood: gangs, people selling drugs, and prostitution. On average, boys observe more of these activities than girls; for example, 32.0% of boys have observed people selling drugs, while this percentage is 23.8% for girls.

2.4 Estimation Strategy

2.4.1 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 given by:

$$Y = \beta T + \gamma X + e .$$

where Y is the outcome of interest (a dummy variable indicating whether an adolescent has dropped out of school), T is the variable of interest (bullying), X is a vector of observed control variables, and e is an error term with mean zero.

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 measurement error. It is well-known that when regressors are measured with random error, the parameters estimated tend to be biased toward 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 e 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. In the case of students who dropped out of school, the questions regarding bullying refer to the time when the adolescents were attending school. A potential 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, it is very unlikely that they will 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 two recently developed bounding methodologies: one developed by Oster (2016) and the other by Krauth (2016). Consider first Oster's (2016) methodology. A common approach to evaluate robustness to omitted variable bias is to include additional control variables on the right hand side of the regression (Altonji et al., 2005). If such additions do not affect the coefficient of interest, then this coefficient can be considered to be reliable. This strategy implicitly assumes that selection on observables is informative about selection on unobservables. Oster (2016) formalize this idea, and provides conditions for bounds and identification. Following the notation in Oster (2016), the full model has the form:

$$Y = \beta\ T + X_1 + X_2 + \epsilon.$$

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 (2016) 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 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.[8] Oster (2016) shows that $\beta^* = \tilde{\beta} - \delta \frac{\left(\beta^0 - \tilde{\beta}\right)\left(R_{max} - \tilde{R}\right)}{\left(\tilde{R} - R^0\right)}$ is a consistent estimator of the effect of T on Y, β.

But, 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 (2016) proposes that $R_{max} = min\{1.3\tilde{R}, 1\}$, where the $\tilde{R}$ is defined above.[9] An alternative value for R_{max} is given by Gonzalez and Miguel (2015), who used

[8] 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.

[9] The cut-off value of 1.3 is derived from a sample of 65 papers that have used randomized controlled trials. She determined that using this cut-off allowed 90% of the randomized results to continue being statistically significant.

$R_{max} = \tilde{R} + (\tilde{R} - R^0)$. In addition to the R_{max} proposed above, I will use a conservative $R_{max} = 1$. After determining the value of R_{max}, Oster suggests that β^* be calculated for all the following ranges of δ: $0 \leq \delta \leq 1$.[10] This allows one to construct the set $[\tilde{\beta}, \beta^*]$ for different values of δ and R_{max}. 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 $\beta^* \neq 0$.

One benefit of Osters bounding methodology is that it provides an intuitive way to arrive at a bounding strategy. However, her approach requires information for two key parameters (R_{max} and δ), and her method does not provide statistical inference about the bounding. Krauths bounding methodology, while more complex has two advantages over Osters methodology. First, it requires information only about δ. Second, it provides inference about the bounding based on Imbens and Manski (2004) confidence intervals. Krauths methodology proceeds using the following model:

Y= Y(T)= β_TT + U

Let $U^P = X_1\beta_{X_1}$ be the best linear predictor of U given X_1 (a group of control variables):

$\beta_{X_1} = E(X_1'X_1)E(X_1'Y) - \beta_T E(X_1'X_1)E(X_1'T)$

Thus:

Y=β_TT + $X_1\beta_{X_1}$ + ϵ, where $E(X_1'\,\epsilon) = 0$

Krauth specifies δ such that:

[10]In addition, I will present the results for δ: $-1 \leq \delta \leq 0$.

$$\frac{Cov(T,\epsilon)}{\sqrt{Var(\epsilon)}} = \delta\frac{Cov(T,X_1\beta_{X_1})}{\sqrt{Var(X_1\beta_{X_1})}}$$

where $\delta \in \Delta = [\delta^L, \delta^H]$, i.e. in a finite interval.

Notice that δ can be rewritten as:

$$\delta(\beta_T) = \frac{corr(T,\epsilon)}{corr(T,X_1\beta_{X_1})} = \frac{corr(T,Y-\beta_T T-X_1\beta_{X_1}(\beta_T))}{corr(T,X_1\beta_{X_1}(\beta_T))}$$

Then, Krauth shows the following properties of $\delta(\beta_T)$:

i. $\delta(\beta_T)$ exists and is differentiable for all $\beta_T \neq \beta^\infty$ (the value of β_T at which $corr(T, X_1\beta_{X_1}(\beta_T)) = 0$).

ii. There is a $\delta^\infty = lim_{\beta_T\to\infty}\delta(\beta_T) = lim_{\beta_T\to-\infty}\delta(\beta_T)$ and $\delta^\infty \geq 0$, i.e. the limit as β_T approaches positive or negative infinity is δ^∞.

iii. Notice that from i and ii, $\delta(\beta_T)$ takes the form of a hyperbolic funtion (see Figure 2.3). Thus, if given the relative correlation restriction $\Delta = [\delta^L, \delta^H]$, the bounds $[\beta_T^L, \beta_T^H]$ can be found by inverting $\delta(\beta_T)$.

See Krauth (2016) for the details of how his approach allows him to obtain the Imbens and Manski (2004) confidence interval for the identified set.

2.5 Results

To analyze the effects of bullying on dropping out of school, I first present the results using an OLS regression, and then apply the two bounding strategies.[11]

[11] The Oster and Krauth strategies use a linear regression, which explains why I use OLS rather than alternatives such as a probit or logit. However, when analyzing the variable of interest (bullying), the results using probit or logit are similar to those using OLS (see Table A2 in appendix).

Table 2.4 column 1, presents a linear probability model (OLS regression) of the impact of bullying on the probability of dropping out of school. I control for father died, mother died, parent in prison, sex, number of siblings, number of siblings who are older, age, and age squared. The results show that one standard deviation increase in being bullied increases the probability of dropping out of school by 5.6 percentage points. To check the robustness of this result, column 2 incorporates dummy variables for states, and column 3 uses dummy variables for municipalities. Bullying continues to be statistically significant, although the impact is slightly diminished.

Given that bullying is measured with error, if this measurement error is random, then the estimates in Table 2.4 underestimate the causal effect and thus are lower bounds of bullying on dropping out of school. However, it is also possible that estimates of the impact of bullying is affected by omitted variable bias. One way to assess this problem is to add controls and analyze the stability of the parameter of interest. Table 2.4, column 4 reproduces the analysis of column 3, but includes more controls. The controls consist of information about girls pregnancies and boys impregnating girls, the feeling of being insecure within their neighborhoods (existence of gangs, people selling drugs, and prostitution), information about self-esteem and health problems (i.e. whether the adolescent has experienced a disease that interferes with his or her activities), and characteristics of the adolescents parents: having authoritative parents, family support, and the alcohol consumption of the mothers and fathers.[12] Bullying continue to be statistically significant. Comparing column 3 with column 4 of Table 2.4, the coefficient associated with bullying decreased from 4.9 to 3.8 percentage points.

[12]I do not have information on alcohol consumption of the mothers and fathers when the father or the mother has died. These missing values were replaced by the average of the respective variables.

Oster (2016) shows that just adding controls, which is a common strategy, is not enough to avoid omitted variable bias. Table 2.5 presents results using Osters methodology to analyze the robustness of the results in Table 2.4. Panel A presents the results under the assumption that $0 \leq \delta \leq 1$, i.e. assuming that 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 (2016), which yields a very tight bounds estimate of [0.055, 0.056]. To check the robustness of this estimate of the bounds, I estimate bounds using the R_{max} proposed by Gonzalez and Miguel (2015) in Column 2. The bounding estimated the same: [0.055, 0.056]. To further check the robustness of the results, I use the extreme value that $R_{max} = 1$, which yields a bounding estimate of [0.045, 0.056] in column 3.

Panel B presents the results when $-1 \leq \delta \leq 0$.[13] Using the R_{max} proposed by Oster, the bounding estimated again is very tight: [0.056, 0.057]. Using the R_{max} proposed by Gonzalez and Miguel, the bounding again is the same: [0.056, 0.057]. Finally, using a conservative $R_{max} = 1$, the bound is: [0.056, 0.067]. To sum up, the effect of bullying on dropping out of school is robust when Osters bounding methodology is used.

Table 2.5, column 4, presents analogous results using Krauths methodology. Assuming that $0 \leq \delta \leq 1$, the bounding associated with bullying is [0.044, 0.056]. However, the 95% confidence interval associated with this estimate is much larger (0.005, 0.081), although it still reject the hypothesis of no effects of bullying on dropping out. If instead one assumes that $-1 \leq \delta \leq 0$, the bounding associated with

[13] The case $-1 \leq \delta \leq 0$ assumes that the relationship between T and X_1 has different sign than the relationship between T and X_2.

bullying is [0.056, 0.065]. The confidence interval at the 95% level associated with bullying is (0.030, 0.094) which again rejects the null hypothesis of no impact of bullying. Finally, I present the value of the minimum δ for which the bounds include zero, being this value 3.234. As a consequence, regardless of which methodology is used, bullying is robust to the problem of omitted variables.

Bullying can potentially have different consequences by sex. Table 2.6 reproduces the results presented in Table 2.4, but differentiates between girls (columns 1 to 3) and boys (columns 4 to 6). For girls, the results show that bullying is statistically significant (see column 1). This result is maintained when dummy variables for states (column 2) and municipalities (column 3) are included. For boys, bullying is statistically significant (see column 4), and this result is maintained when dummy variables for states (column 5) and municipalities (column 6) are included. Yet, the size of the impact for boys is much smaller than for girls.

To analyze the robustness of the effects of bullying on girls probability of dropping out of school, I apply Osters methodology and the results are presented in Table 2.7. Panel A presents the results when $0 \leq \delta \leq 1$. Column 1 use the R_{max} proposed by Oster, the bound on the effect of bullying is [0.102, 0.107]. Using the R_{max} proposed by Gonzalez and Miguel (2015), the bound is [0.102, 0.115]. Finally, using a conservative $R_{max} = 1$, the bound estimated is [0.102, 0.195]. Assuming $-1 \leq \delta \leq 0$, the effects of bullying on the probability of dropping out of the school is presented in Panel B. Using the R_{max} proposed by Oster, the bound estimated is [0.097, 0.102]. Using the R_{max} proposed by Gonzalez and Miguel, the bound is [0.090, 0.102]. Finally, using a conservative $R_{max} = 1$, the bound estimated has a range of [0.010, 0.102]. Thus, bullying is robust to the problem of omitted variables for different assumptions using Osters methodology.

Column 4 in the first panel of Table 2.7 presents the results using Krauths methodology for the effects of bullying on girls' probability of dropping out of school. Assuming $0 \leq \delta \leq 1$, the bound associated with bullying is [0.102, 0.118]. The interval confidence at the 95% level associated with bullying is (0.063, 0.165). In panel B, which assumes $-1 \leq \delta \leq 0$, the bound associated with bullying is [0.087, 0.102]. The 95% confidence interval for the impact of bullying on dropping out of school is (0.029, 0.141). Finally, I present the value of the minimum δ for which the bounds include zero. This value, -9.217, is extremely large. The results using Krauths methodology confirm the previous result, based on Osters methodology, regarding the robustness of the bullying to the problem of omitted variable bias when analyzing its effects on girls probability of dropping out of school.

To analyze the robustness of the results for the case of boys, I again apply Osters methodology. The results are presented in Table 2.8. When $0 \leq \delta \leq 1$ and $R_{max} = 1$, the bound is [-0.021,0.038]. Thus, the estimated bounds include zero. The results using Krauth's methodology are presented in column 4. The estimated bounds for bullying exclude zero. However, when $0 \leq \delta \leq 1$ the confidence interval associated with the variables of interest includes zero. So, in the case of boys, the negative impact of bullying on dropping out is not robust to the problem of omitted variable bias.

2.5.1 Mechanisms

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

Or is bullying increasing the probability of dropping out of school *independent* of the problems associated with the well-being of adolescents?

The psychological literature suggests that being bullied affects students levels of self-esteem, anxiety, and stress. First, I analyze whether these relationships are present in the data, and second, whether these variables are the potential mechanisms by which bullying affects the probability of dropping out of school. Table 2.9 presents an OLS regression of the impacts of bullying on self-esteem (column 1), anxiety (column 2), and stress (column 3). The results confirm the relationship between bullying and these variables. In particular, the results show that a one standard deviation increase in being bullied is associated with 0.15 standard deviation decrease in the self-esteem index; a 0.20 standard deviation increase in the anxiety index; and 0.30 standard deviation decrease in the stress index.

To test whether bullying affects girls probability of dropping out of school through self-esteem, anxiety, stress, and peer relationships, I will use the methodology proposed by Acharia et al. (2016). A common approach to identify mechanisms is simply to control for post-treatment variables, i.e. variables that are believed to be the mechanisms through which the variable of interest is affecting the outcome. In this case the potential post-treatment variables are self-esteem, anxiety, and stress. If the post-treatment variables are significant and they eliminated the significance of the variable of interest (in this case bullying), then we can say that these post-treatment variables are mechanism through which bullying is affecting the outcome of interest. Acharia et al. (2016) present evidence that conditioning on post-treatment variables potentially introduces bias; and in order to handle this problem they propose a sequential g-estimation. The basic idea is that instead of including directly the post-treatment variables on the right hand side, they follow a two-step approach. In the first step, they calculate the effect of the post-treatment variables (mechanism) on the outcome while controlling for the variable of interest (bullying) and other controls. In the second step, they demediate the outcome of interest with the value associated with the post-treatment variable. Finally, they regress the outcome demediated on the variable of interest and the pretreatment confounders.

Figure 2.1 presents the results when self-esteem is considered as a mechanism between bullying and dropping out of school. Model (a) is the baseline model using the covariates presented in Table 2.6. The coefficient associated with bullying is .102. Model (b) presents the results when using the g-estimation model, and the coefficient associated with bullying is .10. Thus, the direct effect of bullying on dropping out of school using the g-estimation is almost identical to the baseline. Figure 2.1 presents the analysis when the mechanism is anxiety. The coefficient associated with bullying is .0970 when using the g-estimator. Finally, Figure 2.2 presents the coefficient associated with bullying when the mechanism is stress and its value is .0979. So, it appears that there is a strong direct effect of bullying on dropouts even if the girls have no problems of self-esteem, anxiety, or stress. Another interpretation of this result is that mechanisms other than those used above have an indirect effect on dropout rates.

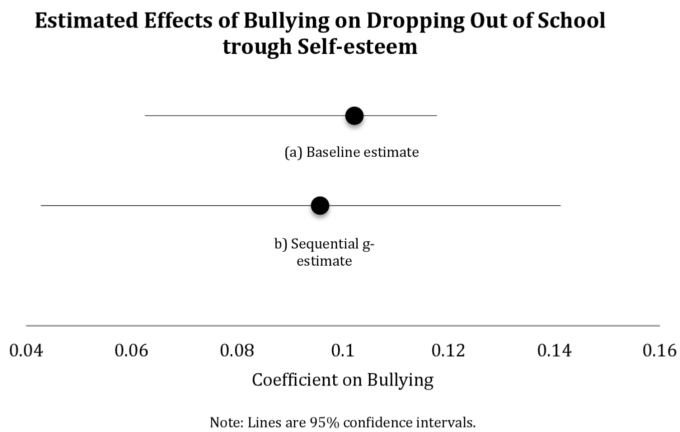
Another important question is what happens with girls after they drop out of school. Do girls, after suffering bullying, end up working outside the home? Or do girls end up neither studying nor working outside the home? Table 2.10 presents results similar to those in Table 2.6, except that the dependent variable is a dummy for girls who neither work nor attend school, and thus it excludes those who work and do not attend school. The regressions are presented in columns 1 to 3. The results show that bullying is statistically significant (see column 1). These results continue to hold when dummy variables for states (column 2) and for municipalities (column 3) are included. Regarding the coefficient associated with bullying, a one standard deviation increase in being bullied increases that probability by 7.2 percentage points. Table 2.10, columns 4 to 6, present results similar to those in columns 1 to 3, except that the dependent variable is a dummy variable for girls who work but do not attend school, and thus it excludes those who neither work nor attend school. Bullying is statistically significant (see column 4). And this result is maintained when dummy variables for states (column 5) and municipalities (column 6) are included. In particular, a one standard deviation increase in bullying increase the probability of working but not attending the school by 5.3 percentage points. Thus, once girl drop out of school as a consequence of bullying, they end working outside the home, but it is also probable that girls end up neither studying nor working outside the home.

2.6 Conclusion

This paper finds evidence that bullying leads to increased drop out rates in adolescents participating in the Mexican conditional cash transfer program PROGRESA, specially among girls. The previous literature that has analyzed this relationship has faced the problem of omitted variable bias. To address this problem, I use two newly developed bounding methodologies one developed by Oster (2016) and the other by Krauth - which provide evidence that the impact of bullying is robust and not simply generated by 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 bullying has more negative consequences on the well-being of girls than on boys. Regarding the mechanisms, I analyze whether bullying affects girls probability of dropping out of school through self-esteem, anxiety and stress. Using a recent methodology developed by Acharia et al. (2016), I do not find strong evidence that self-esteem, anxiety and stress are the mechanisms.

PROGRESA is a successful conditional cash transfer program that has 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 the school for these adolescents; but, on the other hand, it increases the chances that these adolescents suffer from bullying, which may eventually lend them to 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.

Figure 2.1: Estimated Effects of Bullying on Dropping Out of School trough Self-estem and Anxiety



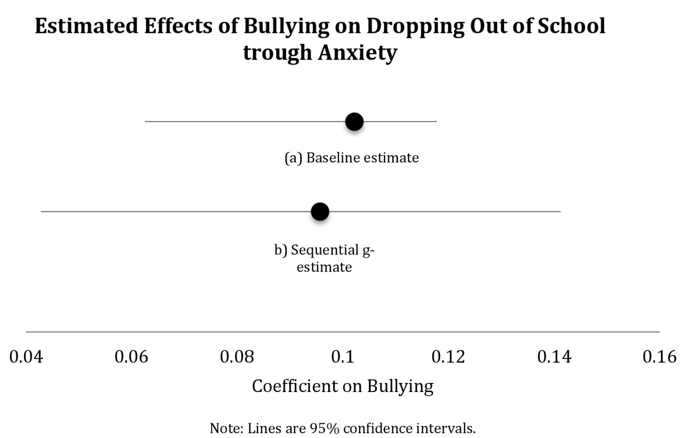


Figure 2.2: Estimated Effects of Bullying on Dropping Out of School trough Stress

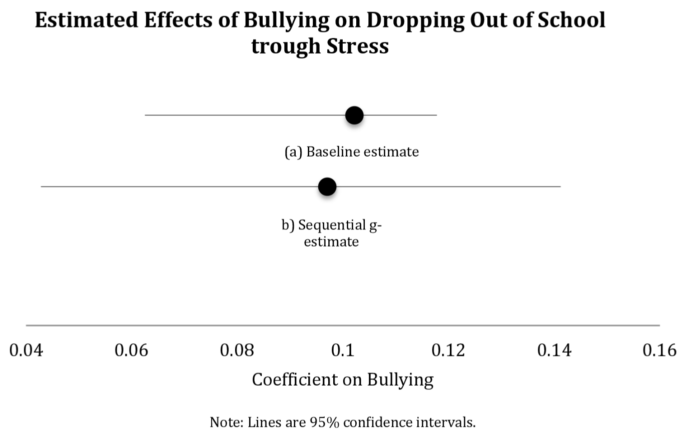


Figure 2.3: A Tipical δ Function

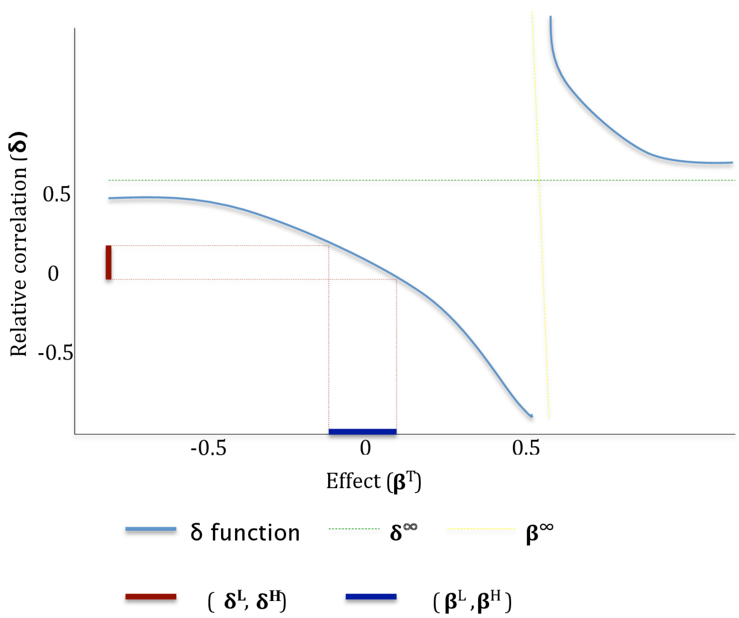


Table 2.1: Causes of School Dropout among Adolescents between 15 and 17 years by Types of Scholarship

	Total %	PROGRESA Scholarship %
Lack of money	39.4	24.0
Lack of interest toward school	10.6	23.6
The student failed some courses	10.6	22.8
Harassment by other students	2.8	11.3
Other	36.6	18.3

Source: Table adapted from Székely (2015)

Table 2.2: Education and Labor Situation among Adolescents between 13 and 16 years old

	Total	Men	Women
All	%	%	%
Studying and not working outside the home	65.4	59.2	73.3
Studying and working outside the home	14.9	21.0	7.2
Working outside the home	11.5	16.5	5.2
Neither studying nor working outside the home	8.2	3.3	14.3
Total	1,091	608	483

Source: Encuesta de resiliencia en beneficiarios de *Oportunidades* .

Table 2.3: Basic Descriptive Statistics

	Total		Girls		Boys	
	Mean	S. D.	Mean	S. D.	Mean	S. D.
Bullying (Std)	0	1	-.184	0.803	0.143	1.109
Self-esteem (Std)	0	1	0.001	0.966	-0.001	1.003
Authoritative parents (Std)	0	1	0.038	0.993	-0.030	1.004
Family support (Std)	0	1	0.051	1.022	-0.040	0.981
Health problems	0.051	0.220	0.066	0.248	0.039	0.194
Parent in prison	0.044	0.207	0.045	0.208	0.044	0.206
Parent died	0.054	0.226	0.053	0.225	0.054	0.226
Pregnancy	0.048	0.215	0.055	0.229	0.042	0.202
Siblings	2.666	1.734	2.612	1.753	2.710	1.720
Siblings older	1.778	1.810	1.769	1.854	1.785	1.776
Mother's alcohol consumption	0.025	0.159	0.031	0.174	0.021	0.145
Father's alcohol consumption	0.246	0.431	0.230	0.421	0.258	0.438
Gangs	0.394	0.488	0.383	0.486	0.402	0.490
People selling drugs	0.284	0.451	0.238	0.426	0.320	0.467
Prostitution	0.194	0.395	0.178	0.382	0.207	0.405
Rural	0.509	0.500	0.496	0.500	0.519	0.500

Source: Encuesta de resiliencia en beneficiarios .

Table 2.4: OLS Estimates: Effects of Bullying on Whether Adolescents Dropped Out of School

	(1)	(2)	(3)	(4)
Dep Var: Dropping Out				
Bullying	0.056***	0.051***	0.049***	0.038***
	(0.011)	(0.012)	(0.012)	(0.012)
Father died	0.238***	0.222***	0.205***	0.203***
	(0.060)	(0.060)	(0.062)	(0.062)
Mother died	0.178*	0.207**	0.173	0.157
	(0.102)	(0.102)	(0.107)	(0.107)
Parent in Prison	0.040	0.024	0.003	-0.007
	(0.054)	(0.054)	(0.057)	(0.057)
Sex (Female=1)	-0.010	-0.010	-0.015	-0.011
	(0.023)	(0.023)	(0.023)	(0.023)
Siblings	0.034***	0.029***	0.029***	0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
Siblings Older	-0.001	0.001	-0.004	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)
Age	0.262	0.271	0.464	0.427
	(0.324)	(0.323)	(0.329)	(0.329)
Age squared	-0.007	-0.007	-0.014	-0.012
	(0.011)	(0.011)	(0.011)	(0.011)
State Fixed Effects	No	Yes	No	No
Municipality Fixed Effects	No	No	Yes	Yes
Other Controls	No	No	No	Yes
R^2	0.12	0.15	0.23	0.25
Observations	981	981	981	980

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. The other controls are: women's pregnancy or men impregnating women (pregnancy), a feeling of being insecure within their neighborhoods (existence of gangs, people selling drugs, and prostitution), self-esteem, health problems, authoritative parents, family support, parents are separated, mother's alcohol consumption, and father's alcohol consumption.

Table 2.5: Bounding Methodology: Effects of Bullying on Whether Adolescents Dropped Out of School

	(1)	(2)	(3)	(4)
	Oster (2016)	Gonzalez and Miguel (2015)	Conservative ($R_{max} = 1$)	Krauth (2016)
		Panel A :	$0 \leq \delta \leq 1$	
Bullying	[0.055, 0.056]	[0.055, 0.056]	[0.045, 0.056]	[0.044, 0.056]
(95% CI)				(0.005, 0.081)
		Panel B :	$-1 \leq \delta \leq 0$	
Bullying	[0.056, 0.057]	[0.056, 0.057]	[0.056, 0.067]	[0.056, 0.065]
(95% CI)				(0.030, 0.094)
Minimum δ for which bounds include zero				3.234

Intervals in squares brackets are the bounds, while the intervals in the round brackets are confidence intervals. The control variables are: father died, mother died, parent in prison, sex, siblings, siblings older, age, age squared, and living in a rural area.

Table 2.6: OLS Estimates: Effects of Bullying on Whether Adolescents Dropped Out of School by Sex

	Girls			Boys		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Dropping Out						
Bullying	0.102***	0.102***	0.088***	0.038***	0.033**	0.038**
	(0.020)	(0.021)	(0.021)	(0.014)	(0.015)	(0.015)
Father died	0.268***	0.237***	0.232***	0.237**	0.230**	0.200*
	(0.075)	(0.077)	(0.084)	(0.095)	(0.097)	(0.103)
Mother died	0.337**	0.402**	0.283	0.103	0.147	0.108
	(0.165)	(0.174)	(0.205)	(0.134)	(0.134)	(0.137)
Parent in Prison	0.044	0.057	-0.028	0.038	0.018	0.033
	(0.080)	(0.082)	(0.091)	(0.073)	(0.074)	(0.077)
Siblings	0.034***	0.028***	0.036***	0.037***	0.030***	0.029***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
Siblings Older	-0.002	-0.000	-0.008	-0.000	0.002	-0.004
	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
Age	-0.096	-0.005	0.027	0.607	0.700	0.920*
	(0.466)	(0.475)	(0.485)	(0.453)	(0.455)	(0.477)
Age squared	0.006	0.003	0.002	-0.019	-0.022	-0.029*
	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)
State Fixed Effects	No	Yes	No	No	Yes	No
Municipality Fixed Effects	No	No	Yes	No	No	Yes
R^2	0.16	0.20	0.35	0.10	0.15	0.24
Observations	429	429	429	552	552	552

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses.

Table 2.7: Bounding Methodology: Effects of Bullying on Whether Adolescents Dropped Out of School (Girls)

	(1)	(2)	(3)	(4)
	Oster	Gonzalez and Miguel	Conservative	Krauth
Indepvar	(2016)	(2015)	($R_{max} = 1$)	(2016)
		Panel A :	$0 \leq \delta \leq 1$	
Bullying	[0.102, 0.107]	[0.102, 0.115]	[0.102, 0.195]	[0.102, 0.118]
(95% CI)				(0.063, 0.165)
		Panel B :	$-1 \leq \delta \leq 0$	
Bullying	[0.097, 0.102]	[0.090, 0.102]	[0.010, 0.102]	[0.087, 0.102]
(95% CI)				(0.029, 0.141)
Minimum δ for which bounds include zero				-9.217

Intervals in squares brackets are the bounds, while the intervals in the round brackets are confidence intervals. The control variables are: father died, mother died, parent in prison, sex, siblings, siblings older, age, age squared, and living in a rural area.

Table 2.8: Bounding Methodology: Effects of Bullying on Whether Adolescents Dropped Out of School (Boys)

	(1)	(2)	(3)	(4)
	Oster (2016)	Gonzalez and Miguel (2015)	Conservative ($R_{max} = 1$)	Krauth (2016)
		Panel A :	$0 \leq \delta \leq 1$	
Bullying	[0.036, 0.038]	[0.032, 0.038]	[-0.021, 0.038]	[0.019, 0.038]
(95% CI)				(-0.022, 0.066)
		Panel B :	$-1 \leq \delta \leq 0$	
Bullying	[0.038, 0.040]	[0.038, 0.044]	[0.038, 0.097]	[0.038, 0.055]
(95% CI)				(0.009, 0.090)
Minimum δ for which bounds include zero				1.919

Intervals in squares brackets are the bounds, while the intervals in the round brackets are confidence intervals. The control variables are: father died, mother died, parent in prison, sex, siblings, siblings older, age, age squared, and living in a rural area.

Table 2.9: OLS Estimates: Effects of Bullying on Self-esteem, Anxiety, and Stress

	(1)	(2)	(3)
Dep Var:	Self-esteem	Anxiety	Stress
Bullying	-0.157**	0.209***	0.300***
	(0.062)	(0.057)	(0.060)
Father died	0.016	0.036	0.062
	(0.229)	(0.213)	(0.225)
Mother died	0.473	-0.413	0.133
	(0.505)	(0.469)	(0.495)
Parent in Prison	0.007	0.258	0.461*
	(0.243)	(0.226)	(0.239)
Siblings	-0.054*	-0.002	-0.016
	(0.031)	(0.029)	(0.030)
Siblings Older	0.030	-0.001	-0.009
	(0.028)	(0.026)	(0.028)
Age	0.703	-0.707	-2.932**
	(1.422)	(1.323)	(1.395)
Age squared	-0.023	0.020	0.099**
	(0.049)	(0.046)	(0.048)
Constant	-5.297	6.076	21.637**
	(10.250)	(9.535)	(10.057)
R^2	0.03	0.06	0.08
Observations	429	429	429

*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses

Table 2.10: OLS Estimates: Effects of Bullying on whether Girls who Dropped Out and end up Working Outside the Home or Neither Studying Nor Working outside the Home

	Work Inside the Home			Work Outside the Home		
	(1)	(2)	(3)	(4)	(5)	(6)
Bullying	0.087***	0.085***	0.072***	0.050***	0.055***	0.053***
	(0.019)	(0.020)	(0.020)	(0.016)	(0.017)	(0.017)
Father Died	0.279***	0.241***	0.271***	0.033	0.043	0.013
	(0.069)	(0.071)	(0.075)	(0.058)	(0.060)	(0.075)
Mother Died	0.385***	0.455***	0.319*	-0.016	-0.055	0.010
	(0.147)	(0.156)	(0.181)	(0.145)	(0.160)	(0.167)
Parent in Prison	0.036	0.051	-0.051	0.015	0.015	0.014
	(0.073)	(0.075)	(0.082)	(0.054)	(0.056)	(0.062)
Siblings	0.007	0.003	0.010	0.037***	0.035***	0.040***
	(0.010)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)
Siblings Older	0.003	0.005	-0.004	-0.006	-0.008	-0.008
	(0.008)	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)
Age	0.044	0.116	-0.052	-0.245	-0.201	0.029
	(0.423)	(0.433)	(0.438)	(0.306)	(0.313)	(0.329)
Age squared	-0.000	-0.002	0.003	0.010	0.008	0.001
	(0.015)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)
Constant	-0.532	-1.150	0.124	1.440	1.077	-0.646
	(3.045)	(3.120)	(3.162)	(2.203)	(2.257)	(2.375)
State Fixed Effects	No	Yes	No	No	Yes	No
Municipality Fixed Effects	No	No	Yes	No	No	Yes
R^2	0.12	0.16	0.35	0.13	0.18	0.27
Observations	410	410	410	386	386	386

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors in parentheses

Chapter 3

What Can Self-Esteem and Self-Control Tell us about Problems in Survey Data?

3.1 Introduction

Among the main instruments for conducting empirical research and making public policy decisions are household surveys; yet, how accurate is the information collected through such surveys? When answering a survey, individuals can have incentives to underreport information. For example, Meyer and Mittag (2015) find evidence that some individuals underreport income in order to get more assistance from the government. But, individuals also can overreport information. Martinelli and Parker (2009) find evidence that overreporting is present when individuals face an embarrassing situation. While there have been some efforts to use statistical tools to identify data abnormalities (e.g. Judge and Schechter, 2009), little attention has been paid to the personality of the individuals who answer surveys. Gottfredson and Hirshi (1990) propose that acts of deviant behavior, such as cheating, are related to low self-control. Thus, people with low self-control are more likely to cheat in a survey. In addition, answering certain types of survey questions can be embarrassing for some individuals.

Embarrassment results when individuals feel negatively about themselves when revealing information that can undermine their image as seen by other people. Recent evidence in psychology has found that embarrassment and self-esteem are strongly related. In particular, Libby et al. (2011) find that individuals with low self-esteem are more likely to misreport information in order to maintain their psychological well-being when facing embarrassing situations. Hence, self-esteem and self-control can be important variables to understand data abnormalities.

Recent literature has found problems in the quality of the data collected, particularly in developing countries. Judge and Schechter (2009) used Benfords law[1] to analyze the quality of the data of nine commonly used datasets, including data from the PROGRESA program in Mexico. They find that the data from Mexico was far from satisfying Benfords law. Unfortunately, Benfords law cannot be applied to binary or categorical data but which are fundamental for understanding many aspects of household behavior and welfare, such as the possession of assets.

To understand how self-esteem and self-control explain data anomalies, I use a unique database that asks the same questions of the wife and of the husband regarding both psychological variables and the possession of assets in 903 households in Mexico. The questions regarding assets are dummy variables, i.e. do you have a refrigerator in your household? The results show important discrepancies between the information reported by the wife and by the husband. For example, when asked about the possession of a washing machine, the information reported by the spouses did not coincide in 24% of the households. To understand the differences in the answers provided by the wife and the husband, I generate: an index for the differences

[1] The idea behind Benfords law is that, in large data sets, numbers with a first digit of 1 are observed more often than those starting with 2 and so on. In particular, Benfords law proposes that: P(first digit is d)= $log_{10}(1 + \frac{1}{d})$.

in the possession of assets; an index of self-esteem based on the Rosenberg Self-esteem Scale (1965); and an index of self-control based on the Self-Regulatory Questionnaire (SQR) of Brown, et. al. (1999).[2] Ordinary Least Squares results show that self-esteem and self-control explain the differences in the possession of assets reported. In particular, a one standard deviation increase in the square of husbands self-esteem reduces by 0.065 standard deviations an index regarding the differences of assets reported by each spouse. In addition, a one standard deviation increase in the square of husbands self-control reduces by .070 standard deviations an index regarding the differences of assets reported by each spouse.

Estimating the effects of self-esteem and self-control on the differences in the assets reported between the husband and the wife is complicated by problems of measurement error and omitted variable bias. If measurement errors in the self-esteem and self-control variables are random, then the estimates of the impacts of self-esteem and self-control on an index regarding the differences of assets reported by each spouse underestimate the causal effect and thus they represent a lower bound on the true effect. Regarding omitted variable bias, self-esteem and self-control may be correlated with other psychological variables (or non psychological variables) not present in the data. If such variables are correlated with the outcome of interest, then they are in the error term and their correlation with self-esteem and/or self-control will generate bias in the estimated impacts of those two variables. To assess the problem of omitted variables, I use two recently developed bounding methodologies: one developed by Oster (2016) and the other by Krauth (2016). Their strategies assume that adding observed control variables is informative about the bias due to unobservable variables and, based on this assumption, conditions for bounds and identification are provided. My results suggest that the estimates of self-esteem and self-control are not robust

[2] All the indices were standardized to have a mean of zero and a standard deviation of one.

to omitted variable bias.

Asset information is frequently used to do empirical research, and to guide public policy, such as deciding who participates in social programs and/or generating measures of poverty. For example, many social programs use a proxy means test to decide who participates in the program. Policy makers recognize that individuals have incentives to underreport their income, and as a consequence, they have developed proxy means tests as an alternative to collecting information on income. An important element of these proxy means tests is the possession of assets. Yet, the results of this paper show that information on assets can also be biased and potentially affect who is eligible to participate in the program.

The rest of the paper is organized as follows: Section 2 reviews the related literature; Section 3 introduces the data, and Section 4 describes the empirical strategy; Section 5 presents the results; and Section 6 concludes.

3.2 Literature Review

Philipson and Malani (1999) point out that economists pay much more attention to the consumption of data than to the production of data. Judge and Schechter (2009) mention that this point is consistent with the increasing literature on how to handle problems of measurement errors, but little literature on how to prevent it. Philipson and Malani (1999) propose that the data collection process can be analyzed as a labor market where the investigator is the principal and the individuals who provide information are the agents. The problem is that the agents have preferences (does the respondent want to tell the truth?) and problems of information (does the respondent know the truth?). This situation is the principal source of erroneous reporting. Thus, researchers and policy makers should be careful when empirical data are used.

So, if there is a potential problem of erroneous reporting, how can one check the quality of the data? Judge and Schechter (2009) proposed that Benfords law can be used as a tool to detect problems in survey data. The idea behind Benfords law is that, in large data sets, numbers with a first digit of 1 are observed more often than those starting with 2, and so on. In particular, Benfords law proposes that: P(First digit is d)= $log_{10}(1 + \frac{1}{d})$. Judge and Schechter (2009) analyzed data from nine commonly used datasets, including the Matlab Health and Socioeconomics Survey (MHSS) from Bangladesh, the PROGRESA data from Mexico, the Living Standards Measurement Survey (LSMS) from Peru, the Agricultural Resource Management Survey (ARMS) from the United States, among others. Their principal result is that the data from developing countries are of poor quality based on Benfords law, and the data from the United States are of better quality. In addition, they reported no differences between female and male respondents.

Yet, there is a problem with Benfords law. Many variables used for data analysis are dummy or categorical variables, and Benfords law cannot be applied in such cases. However, it is possible to assess data quality for dummy and categorical variables. For example, Martinelli and Parker (2009), using data from PROGRESA, find evidence of misreporting and overreporting when analyzing dummy and categorical variables. When the program was expanded from rural to urban areas (2002), the applicants first attended a registration meeting, and provided information in order to participate in the program. From those who were eligible based on a household poverty index, the program sent a representative to their house in order to verify the information provided at the registration meeting. Martinelli and Parker (2009) compared these sources of information, and they find underreporting in gas boilers, cars, trucks, and washing machines; and they present evidence of overreporting in toilets, tap water, and concrete floor. Thus, at least for the PROGRESA program, the dummy variables are not free from measurement error.

Why do individuals not report the truth? In economic terms, it can be assumed that individuals make a cost-benefit analysis. For example, individuals can consider the potential benefits (such as access to a social program) of cheating (underreporting information) and the cost of cheating (probability of being discovered and the potential penalties). Mazar and Ariely (2006) present evidence that in addition to the external reward mechanisms (cost-benefit analysis), there are internal reward mechanisms that affect the decisions of individuals regarding cheating. What other aspects do individuals consider in addition to material payoffs? Gottfredson and Hirshi (1990) propose that acts of deviant behavior, such as cheating, are related to low self-control. In particular, people with lack of self-control tend to be impulsive, risk-taking, and succumb to the desires of the moment. These elements are important predictors for engaging in a deviant behavior. In particular, Gottfredson and Hirshi (1990) argue that people value the desire to maximize self-interest (short-term) versus the desire of being an honest person (long-term). This implis that people with high self-control resist short-term temptations. Thus, it is plausible that people with low levels of self-control are more likely to cheat in a survey.

Yet, Gino, Schweitzer, Mad, and Ariely (2011) propose that, under some circumstances, people with high levels of self-control can also cheat. They propose that, despite having self-control, monitoring many decisions reduces peoples moral awareness, with the consequence of increasing the probability of cheating. To present evidence of this hypothesis, they conducted experiments with college and graduate students. The students were separated into two groups. The first group was asked to write an essay without using the letters A and N and the other the letters X and Z. The first group (under “depletion condition) required more effort, i.e. their cognitive condition were more “taxed. Then, the students solved a set of problems on the computer, and they self-report their performance. This task was intended to give the students the opportunity to cheat. The results show that participants cheated more when they were included in the “depletion condition group. Why is this result important for the present research? When answering a survey, it is possible that the cognitive ability of the individuals is “taxed by trying to answer all the questions that need to be answered. Increasing the probability that, as individuals with low self-control, individuals with high levels of self-control end up cheating. This leads to a situation where self-control will not be able to explain potential discrepancies in the survey conducted.

Regarding self-esteem, Tyler and Feldman (2005) find evidence that the accuracy of the information is tied with self-esteem. For example, when facing an embarrassing situation, individuals with low self-esteem are more likely to change how the situation looks in order to maintain their psychological well-being (Libby, Eibach, Valenti, and Pfent, 2011) and present misleading information in order to influence others point of view about themselves (Godfrey, Jones, and Lord, 1986). Hence, self-esteem can be an important variable for identifying data abnormalities.

3.3 Data

To analyze the effects of self-esteem and self-control on the differences in the possession of assets reported by the wife and the husband, I use a database from couples participating in Mexico's PROGRESA conditional cash transfer program. The survey collected information from 903 couples on non-cognitive skills and socioeconomic information. To analyze the quality of the data, I follow Judge and Schechter (2009), and I use a χ^2 test to check the extent to which the data conform with Benfords law. The results are presented in Table 3.1 and the variables that I analyze are income, light bulbs and number of rooms. Separately by the gender of the respondent, for the three variables analyzed I reject the null hypothesis that the data follow Benfords law. This opens the possibility that the data contain abnormalities.

As pointed out above, Benfords law cannot be applied to the analysis of dummy variables. So, what is the quality of the PROGRESA data regarding the possession of assets, which are represented by dummy variables? Table 3.2, column 1, shows the possession of assets reported by husbands and column 2 those reported by wives. There are no important discrepancies when comparing column 1 and 2. For example, 63.5% of the husbands reported the possession of a refrigerator in their houses, while this percentage is 65.1% for wives. One tentative interpretation of this result is that when asked information regarding dummy variables the information collected is not so bad, in contrast to the results for Benfords law. Column 3 presents the percentage of mismatch regarding the 18 items, i.e. the percentage of cases when the information provided by husbands did not coincide with the information provided by wives. This suggest problems with the quality of the data collected. For example, in the case of having a refrigerator, for 21.3% of the couples the information provided by the husband did not match the information provided by the wife. In particular, for 9.8% of the cases, the husband responded that the household had a refrigerator and the wife replied that the household was not in a possession of a refrigerator (see column 4); and for 11.5% the husband responded that the household was not in a possession of a refrigerator while the wife responded that the household had a refrigerator (see column 5). The percentage when there is a mismatch goes for 2.2% in the case of having a canoe up to 32.9% for the case of having a music device (see column 3). Yet, the percentage of mismatching is lower than 10% in the cases when the assets are present in a high proportion (like having a TV) or when the assets are almost absent in the majority of the households (like having a canoe).

Table 3.3 presents aggregate information about the asset ownership reported by the wife and the husband. For the 18 items asked, the number of discrepancies between the wife and the husband ranges from 0 (perfect coincidence) to 12. For example, for 13.8% of the couples, the information reported by the wife and the husband coincided exactly. Yet, Table 3.3 also presents evidence that in 15% of the couples, the answers reported were different for 5 or more of the 18 items.

Regarding the variables of interest, I develop an index of self-esteem and an index of self-control based on principal components. The self-esteem index used is based on Rosenberg (1965) and the self-control index is based on Brown, et al. (1999); both adapted by Palomar (2015) for the case of Mexico. The questions used have the following categorical answers: “always, “frequently, “rarely and “never. I aggregate the answers into scales using principal components analysis, retaining only the first latent factor. I present the results of the principal components analysis in Table 3.4. Column 1 presents the eigenvalues, Column 2 presents the questions used to build the scales, 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.

3.4 Estimation Strategy

3.4.1 Identification Strategy

This paper analyzes the effects of self-esteem and self-control on the differences in the possession of assets reported by the wife and the husband from couples participating in PROGRESA. Ideally, I would like to estimate the following equations for the husband (h) and the wife (w):

$$Y_j^h \text{ - } Y_j^r = \beta_{1h}T_{hj}+\beta_{2h}T_{hj}^2+\gamma_h X_{hj}+e_{hj} \quad \text{(1a)}$$

$$Y_j^w \text{ - } Y_j^r = \beta_{1w}T_{wj}+\beta_{2w}T_{wj}^2+\gamma_w X_{wj}+e_{wj} \quad \text{(1b)}$$

where Y_j^i is an index adding assets reported by individual i in house j, Y_j^r is and index adding the real (truthful) number of assets within the household, T_{ij} is the self-esteem (or self-control) of the individual i in house j, X is a vector of observed control variables, and e is an error term with mean zero. Unfortunately, I cannot observe Y_j^r, however, I can still estimate all the parameters in equations (1a) and (1b) by taking the differences, to obtain the following specification:

$$Y_j^m \text{ - } Y_j^w=\beta_{1h}T_{hj} \text{ - } \beta_{1w}T_{wj} + \beta_{2h}T_{hj}^2\text{ - } \beta_{2w}T_{wj}^2 + \gamma_h X_{hj} - \gamma_w X_{wj} + e_{hj} \text{ - } e_{wj}$$
(1c)

The parameters of interests are β_{1i} and β_{2i}. The estimate of β_{1i} is a test for the hypothesis of a linear relationship between the variable of interest (self-esteem or self-control) and the real number of assets reported. For example, in the case of self-esteem, if this coefficient is negative and statistically significant, it implies that as self-esteem increases the difference between the assets reported by the individual and the real number of assets within the household coincide. Similarly, β_{2i} tests for the hypothesis that there is a non-linear relationship between the variable of interest (self-esteem or self-control) and the dependent variable. For example, if this coefficient is negative and statistically significant, then it implies that the difference between the assets reported by the individual and the real number of assets within the household coincide when the individual has higher levels or lower levels of self-esteem (self-control).

A study of this type presents several econometric challenges. First, the measures of self-esteem and self-control are proxy variables, so there is a potential problem of measurement error. It is well-known that when regressors are measured with random error, the parameters estimated tend to be biased toward zero. Second, self-esteem and self-control may be correlated with other psychological variables not present in the data. If such variables have a causal impact on the outcome of interest, then they are in the error term e and their correlation with T will generate bias in the estimated impacts of self-esteem or of self-control. On a more positive note, reverse causality is likely to be minimal. In particular, there is little or no reason why the difference in the assets reported can affect the self-esteem and self-control of the individuals.

To address the problem of omitted variable bias, I use two recently developed bounding methodologies: one developed by Oster (2016) and the other by Krauth (2016). Consider first Oster's methodology. A common approach to evaluate robustness to omitted variable bias is to include additional control variables on the right hand side of the regression (Altonji et al., 2005). If such additions do not affect the coefficient of interest, then this coefficient can be considered to be unlikely to be biased. This strategy implicitly assumes that selection on observables is informative about selection on unobservables. Oster formalizes this idea, and provides conditions for bounds and identification. Following the notation in Oster, the full model has the form:

$$Y= \beta\ T+ X_1 + X_2 +\epsilon. \tag{2}$$

where T is the variable of interest, X_1 contains the J_o *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 J_u *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 (2016) 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 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.[3] Oster shows that $\beta^* = \tilde{\beta} - \delta \frac{\left(\beta^0 - \tilde{\beta}\right)\left(R_{max} - \tilde{R}\right)}{\left(\tilde{R} - R^0\right)}$ is a consistent estimator of the effect of T on

[3]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.

Y, β.

But, to estimate β^*, one needs estimates of δ and R_{max}. Oster proposes assumptions for δ and R_{max} that allow 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 as above.[4] An alternative value for R_{max} is given by Gonzalez and Miguel (2015), who used $R_{max} = \tilde{R} + (\tilde{R} - R^0)$. In addition to these two methods to choose the R_{max}, I will also use a conservative $R_{max} = 1$. After determining the value of R_{max}, Oster suggests that β^* be calculated for the following ranges of δ: $0 \leq \delta \leq 1$.[5] This allows one to construct the set $[\beta^*(\delta = 0), \beta^*(\delta = 1)]$ for different values of R_{max}. 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 $\beta^* \neq 0$.

One benefit of Osters bounding methodology is that it provides an intuitive way to arrive at a bounding strategy. However, her approach requires information for two key parameters (R_{max} and δ), and her method does not provide statistical inference about the bounding. Krauths bounding methodology, while more complex, has two advantages over Osters methodology. First, it requires information only about δ. Second, it provides inference about the bounding based on Imbens and Manski (2004) confidence intervals. Krauths methodology proceeds using the following model:

$$\text{Y} = \text{Y(T)} = \beta_T \text{T} + \text{U} \tag{3}$$

Let $U^P = X_1 \beta_{X_1}$ be the best linear predictor of U given X_1 (a group of control

[4] The cut-off value of 1.3 is derived from a sample of 65 papers that have used randomized controlled trials. She determined that using this cut-off allowed 90% of the randomized results to continue being statistically significant.

[5] In addition, I will present the results for δ: $-1 \leq \delta \leq 0$.

variables):

$\beta_{X_1} = E(X_1'X_1)E(X_1'Y) - \beta_T E(X_1'X_1)E(X_1'T)$

Thus:

Y=β_TT + $X_1\beta_{X_1}$ + ϵ, where $E(X_1'\,\epsilon) = 0$ (4)

Krauth specifies δ such that:

$$\frac{Cov(T,\epsilon)}{\sqrt{Var(\epsilon)}} = \delta\frac{Cov(T,X_1\beta_{X_1})}{\sqrt{Var(X_1\beta_{X_1})}} \quad (5)$$

where $\delta \in \Delta = [\delta^L, \delta^H]$, i.e. in a finite interval.

Notice that δ can be rewritten as:

$$\delta(\beta_T) = \frac{corr(T,\epsilon)}{corr(T,X_1\beta_{X_1})} = \frac{corr(T,Y-\beta_T T-X_1\beta_{X_1}(\beta_T))}{corr(T,X_1\beta_{X_1}(\beta_T))} \quad (5')$$

Then, Krauth shows the following properties of $\delta(\beta_T)$:

i. $\delta(\beta_T)$ exists and is differentiable for all $\beta_T \neq \beta^\infty$ (the value of β_T at which corr$(T, X_1\beta_{X_1}(\beta_T)) = 0)$.

ii. There is a $\delta^\infty = lim_{\beta_T\to\infty}\delta(\beta_T) = lim_{\beta_T\to-\infty}\delta(\beta_T)$ and $\delta^\infty \geq 0$, i.e. the limit as β_T approaches positive or negative infinity is δ^∞.

iii. Notice that from i and ii, $\delta(\beta_T)$ takes the form of a hyperbolic funtion. Thus, if given the relative correlation restriction $\Delta = [\delta^L, \delta^H]$, the bounds $[\beta_T^L, \beta_T^H]$ can be found by inverting $\delta(\beta_T)$.

See Krauth (2016) for the details of how his approach allows him to obtain the Imbens and Manski (2004) confidence interval for the identified set.

3.5 Results

To analyze the effects of self-esteem and self-control on explaining the differences in the assets reported by the wife and the husband, I first present results using an OLS regression, and then apply the two bounding strategies.

Column 1 of Table 3.5 presents a linear model (OLS regression) of the impact of husbands' self-esteem and wives' self-esteem, and their squares on the difference in the assets reported. I control for husband's age, wife's age, and their squares, husband's years of school, wife's years of school, and their squares. The results show that a one standard deviation increase in the square of husband's self-esteem decreases the index of differences in assets (this index has a mean of zero and a standard deviation of one) by 0.065 standard deviations.

To check the robustness of this result, column 2 incorporates the following additional controls for the wife and the husband: "error in the number of dependents", perception of households level of poverty, alcohol consumption, and living in a rural area. "Error in number of dependents" is a dummy variable that measures inconsistencies in the number of households members reported. This variable was generated by first asking about the number of household members. Then, after some questions were answered, information was asked regarding the number of children less than 12 years old and the number of adults above 65 years old. The variable "error in the number of dependents" takes the value of one when the number of children less than 12 years old plus the number of adults more than 65 years old is above the number of members originally reported, and it takes the value of zero otherwise. The idea behind this variable is to try to identify cases when the respondents are not paying enough attention when answering the survey.

The questions regarding the consumption of alcohol was included because this question reflects a potentially embarrassing situation. So, individuals who reveal having a problem of alcohol consumption potentially have a strong self-esteem. Finally, a question was included regarding the perception of households level of poverty. In particular, the question asks: "comparing your home with all Mexican households, and on a scale of 1 to 10, where 1 is the poorest and 10 the richest, what number would you give to your home?" Remember that the survey was collected among families participating in PROGRESA, which are living in poverty. So, if the wife or the husband respond that they are in the highest deciles, one might expect that some of the information they are revealing may be inconsistent. After including these controls, the square of husbands self-esteem has the same effect (-0.065) and continues to be statistically significant.

Column 3 of Table 3.5 presents a linear model (OLS regression) of the impact of the husband's self-control and the wife's self-control, and their squares, on the difference in the assets reported. Using the same controls as those in column 1 of Table 3.5, the results show that a one standard deviation increase in the square of husband's self-control decreases by 0.62 standard deviations the index of the differences in assets; and, this coefficient is statistically significant. To check the robustness of this result, column 4 incorporates the control variables used in Table 3.5 column 2. This leads to an increase in the effect of the square of husbands self-control (-0.069), which continues to be statistically significant.

Column 5, presents a linear model of the impact of the eight variables of interest (self-esteem, self-control, self-esteem to the square, and self-control to the square for both spouses) on the difference in the assets reported. Using the same controls as those in Columns 2 and 4 of Table 3.5, the results confirm that the coefficients associated with the square of husbands self-esteem and the square of husbands self-control continue being statistically significant.

While the coefficients associated with self-esteem and self-control appear to be robust to adding control variables, it is also possible that these estimates are affected by omitted variable bias. In particular, Oster (2016) shows that just adding controls, which is a common strategy, is not enough to avoid omitted variable bias. Table 3.6 presents results using Oster's methodology to analyze the robustness of the results presented in Table 3.5 Column 3 regarding self-esteem and self-control.

Panel A presents the results under the assumption that $0 \leq \delta \leq 1$, i.e. assuming that 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. The Column 1 estimates bounds using the value of the R_{max} proposed by Oster (2016), which yields a tight bounds estimate of [-0.074, -0.065]. To check the robustness of this estimate of the bounds, I also estimate bounds using the R_{max} proposed by Gonzalez and Miguel (2015) in Column 2. The bounding estimated is [-0.093, -0.065]. To further check the robustness of the results, I use the extreme value that $R_{max} = 1$, which yields a bounding estimate of [-1.106, -0.065] in Column 3 of Table 3.6. Thus, when the correlation of the self-esteem with the observed control variables is assumed to be the same sign as the correlation with the unobserved control variables, Oster's method shows that the result on self-esteem in Table 3.5 is robust.

Panel B presents the results when $-1 \leq \delta \leq 0$.[6] Using the R_{max} proposed by Oster, the bounding estimated is [-0.065, -0.055]. Using the R_{max} proposed by Gonzalez and Miguel, the bounding is [-0.065, -0.036]. Finally, using a conservative $R_{max} = 1$, the bound is [-0.065, 1.037].

Table 3.6, Column 4 panel A, presents analogous results using Krauth's methodology. Assuming that $0 \leq \delta \leq 1$, the bounding associated with self-esteem is [-0.804, -0.065]; and the 95% confidence interval associated with this estimate is (-1.070, -0.935). Thus, the hypothesis of no effects of self-esteem on explaining the difference in the assets reported by the wife and the husband is not rejected. If instead one assumes that $-1 \leq \delta \leq 0$, the bounding associated with self-esteem is [-0.065, -0.006]. The confidence interval at the 95% level associated with self-esteem is (-0.114, 0.047) which fails to reject the hypothesis of an impact of self-esteem. Finally, I present the value of the minimum δ for which the bounds include zero; this value is 1.86. As a consequence, regardless of the methodology used, the impact of self-esteem (i.e. the the square of husbands self-esteem) is not robust to the problem of omitted variable bias.

Panels C and D present the results for the square of husband's self-control. Under the assumption that $0 \leq \delta \leq 1$, Column 1 estimates bounds using the value of the R_{max} proposed by Oster (2016), which yields a tight bounds estimate of [-0.081, -0.069]. To check the robustness of this estimate of the bounds, I also estimate bounds

[6] The case $-1 \leq \delta \leq 0$ assumes that the correlation between T and X_1 has different sign than the correlation between T and X_2.

using the R_{max} proposed by Gonzalez and Miguel (2015) in Column 2. The bounding estimated is [-0.106, -0.069]. To further check the robustness of the results, I use the extreme value that $R_{max} = 1$, which yields a bounding estimate of [-1.521, -0.069] in Column 3 of Table 3.6. Thus, when the correlation of the square of husbands self-control with the observed control variables is assumed to be the same sign as the correlation with the unobserved control variables, Oster's method shows that the result on self-control in Table 3.5 is robust.

Panel D presents the results when $-1 \leq \delta \leq 0$. Using the R_{max} proposed by Oster, the bounding estimated is [-0.069, -0.057]. Using the R_{max} proposed by Gonzalez and Miguel, the bounding is [-0.069, -0.032]. Finally, using a conservative $R_{max} = 1$, the bound is [-0.069, 1.383]. To sum up, when the correlation between the square of husband self-control and the observed control variables has the opposite sign of the correlation of the square of husband self-control with the unobserved variables, the effect of self-control on the differences in the assets reported is not robust when Oster's bounding methodology is used.

Table 3.6, Column 4 panel C, presents analogous results using Krauth's methodology. Assuming that $0 \leq \delta \leq 1$, the bounding associated with the square of husband self-control is [-0.605, -0.069]; and the 95% confidence interval associated with this estimate is (-0.786, 1.028). Thus, the hypothesis of no effect of self-control on explaining the difference in the assets reported by the wife and the husband is not rejected. If instead one assumes that $-1 \leq \delta \leq 0$, the bounding associated with self-control is [-0.069, 0.017]. The confidence interval at the 95% level associated with self-control is (-0.129, 0.104) which again rejects the hypothesis of an impact of self-control. Finally, I present the value of the minimum δ for which the bounds include zero; this value is 0.57. As a consequence, regardless of the methodology used, the impact of self-control (i.e. the square of husbands self-control) is not robust to the problem of omitted variable bias.

3.6 Summary and Concluding Remarks

I use a unique dataset that asks the same questions of the wife and of the husband regarding the possession of assets; and I find discrepancies in the possession of assets reported between the spouses. Using Ordinary Least Squares, the results show that husbands self-esteem and self-control are important variables that affect such discrepancies. The results are robust to the problem of omitted variables when Oster's bounding methodology is implemented, but not when Krauth's methodology is implemented.

Researchers and policy makers need to be careful about how the data are used. For example, when using data to construct a proxy means test, policy makers recognize that individuals have incentives to underreport income. As a consequence, they use variables such as the possession of assets to proxy the real income of the households. It is assumed that there are no incentives to misreport these variables. Yet, this paper presents evidence that contradicts this assumption. In this sense, it is necessary to implement strategies that can provide incentives to individuals to accurately report the data.

Table 3.1: χ^2 Tests Between Benford's Law and Some Items

Variable	χ^2 man	χ^2 woman
Income	167.6 ***	157.2 ***
Light bulbs	523.3 ***	623.43 ***
Number of rooms	599.4 ***	619.7 ***

***** indicates 99% significantly different from Benford's Law.*

Table 3.2: Descriptive Statistics

	Husband's report of possession of (%):	Wife's report of possession of (%):	Percentage that do not match (%)	Husband: Yes Wife: No	Husband: No Wife: Yes
Music device	59.7	57.5	32.9	17.5	15.4
Bicycle	42.7	36.5	30.2	18.3	11.9
Farm animals	29.6	31.0	25.6	12.1	13.5
Washing Machine	42.7	43.1	24.0	11.8	12.2
Gas stove	20.0	21.8	22.9	10.7	12.2
Refrigerator	63.5	65.1	21.3	9.8	11.5
Living room	23.7	23.0	18.7	9.7	9.0
Automobile	19.4	16.2	13.7	8.5	5.2
Landline	15.7	16.6	13.5	6.3	7.2
Photographic camera	8.4	6.6	10.9	6.4	4.5
Other land	8.3	6.5	10.7	6.3	4.4
Television	90.9	90.6	8.4	4.4	4.0
Machinery	5.5	3.0	7.0	4.8	2.2
Apartment to rent	4.3	3.7	7.0	3.8	3.2
Motorcycle	5.2	5.5	5.6	2.6	3.0
Savings	1.9	3.6	4.9	1.5	3.4
Local business	2.7	2.8	3.6	1.7	1.9
Canoe or boat	2.0	1.7	2.2	1.2	1.0

Table 3.3: Distribution Across Households for the Number of Assets for which There Is No Match

Number	Freq.	Percent.	Cum.
0	121	13.80	13.80
1	154	17.56	31.36
2	190	21.66	53.02
3	157	17.90	70.92
4	124	14.14	85.06
5	55	6.27	91.33
6	41	4.68	96.01
7	24	2.74	98.75
8	4	0.46	99.20
9	3	0.34	99.54
10	1	0.11	99.66
11	1	0.11	99.77
12	2	0.23	100.00

Table 3.4: Latent Variable Scales

Scale Name	Scale Survey Question	Factor Loadings
Self-esteem	[1] I am satisfied with myself	0.3856
Eigenvalue: 2.4	[2] I am able to do things as well as others	0.4345
	[3] I am a worthy person	0.4741
	[4] I have good qualities	0.4620
	[5] I have a positive attitude toward myself	0.4736
Self-control	[1] You make decisions carefully	0.3158
Eigenvalue: 4.6	[2] You finish what you start	0.3203
	[3] You have a lot of will power	0.3160
	[4] You evaluate your progress when you set a goal	0.3341
	[5] You can mantain a plan from start to finish	0.3337
	[6] You think before you react	0.3088
	[7] You keep your goals	0.3297
	[8] You strive to achieve your goals	0.3518
	[9] You comply with what is deemed necessary in order to achieve your goal	0.2882
	[10] You overcome fear when facing a challenge	0.2530

Table 3.5: OLS Estimates: Effects of Self-esteem and Self-control on the Index of Differences in Assests

	(1)	(2)	(3)	(4)	(5)
Dep Var: Index of differences in assets					
Husband's Self-esteem	-0.068	-0.064			-0.062
	(0.050)	(0.049)			(0.045)
(Husband's Self-esteem)^2	-0.065**	-0.065***			-0.063***
	(0.025)	(0.024)			(0.023)
Wife's Self-esteem	0.013	0.012			0.013
	(0.046)	(0.044)			(0.044)
(Wife's Self-esteem)^2	0.038	0.038			0.042
	(0.029)	(0.030)			(0.030)
Husband's Self-control			-0.065	-0.056	-0.050
			(0.052)	(0.052)	(0.052)
(Husband's Self-control)^2			-0.062*	-0.069**	-0.068**
			(0.032)	(0.033)	(0.033)
Wife's Self-control			-0.031	-0.042	-0.042
			(0.039)	(0.039)	(0.044)
(Wife's Self-control)^2			-0.030	-0.033	-0.039
			(0.026)	(0.026)	(0.028)
Husband's Age	-0.045**	-0.039*	-0.049**	-0.045**	-0.043*
	(0.021)	(0.022)	(0.021)	(0.022)	(0.023)
(Husband's Age)^2	0.000*	0.000	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wife's Age	0.039	0.037	0.032	0.034	0.037
	(0.028)	(0.030)	(0.027)	(0.029)	(0.031)
(Wife's Age)^2	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Husband's Years of School	0.033	0.037	0.022	0.029	0.039
	(0.023)	(0.023)	(0.022)	(0.022)	(0.024)
(Husband's Years of School)^2	-0.003	-0.003	-0.001	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wife's Years of School	0.004	0.005	-0.001	-0.000	-0.002
	(0.026)	(0.025)	(0.027)	(0.025)	(0.026)
(Wife's Years of School)^2	-0.000	-0.000	-0.000	-0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Other Controls	No	Yes	No	Yes	Yes
R^2	0.02	0.03	0.02	0.03	0.04
Observations	855	837	857	839	803

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses

The other controls are: living in a rural area, wife and husband's perception of household's level of poverty, wife and husband's error in the number of dependents, and alcohol consumption.

Table 3.6: Bounding Methodology: Effects of Husbands Self-esteem and Self-control on the Index of Differences in Assets

	(1)	(2)	(3)	(4)
	Oster (2016)	Gonzalez and Miguel (2015)	Conservative ($R_{max} = 1$)	Krauth (2016)
		Panel A :	$0 \leq \delta \leq 1$	
(Husband's Self-esteem)^2	[-0.074, -0.065]	[-0.093, -0.065]	[-1.166, -0.065]	[-0.804, -0.065]
(95% CI)				(-1.070, 0.935)
(90% CI)				(-1.027, 0.891)
		Panel B :	$-1 \leq \delta \leq 0$	
(Husband's Self-esteem)^2	[-0.065, -0.055]	[-0.065, -0.036]	[-0.065, 1.037]	[-0.065, -0.006]
(95% CI)				(-0.114, 0.047)
(90% CI)				(-0.106, 0.038)
Minimum δ for which bounds include zero				1.86
		Panel C :	$0 \leq \delta \leq 1$	
(Husband's Self-control)^2	[-0.081, -0.069]	[-0.106, -0.069]	[-1.521, -0.069]	[-0.605, -0.069]
(95% CI)				(-0.786, 1.028)
(90% CI)				(-0.757, 0.920)
		Panel D :	$-1 \leq \delta \leq 0$	
(Husband's Self-control)^2	[-0.069, -0.057]	[-0.069, -0.032]	[-0.069, 1.383]	[-0.069, 0.017]
(95% CI)				(-0.129, 0.104)
(90% CI)				(-0.119, 0.090)
Minimum δ for which bounds include zero				0.57

Intervals in brackets are the bounds, while the intervals in parentheses are confidence intervals. The control variables are: Husband's Self-esteem, Wife's Self-esteem, Husband's Self-control, Wife's Self-control, Husband's Age, Wife's Age, Husband's Age to the square, Wife's Age to the square, Husband's Years of School, Wife's Years of School, Husband's Years of School to the square, Wife's Years of School to the square, wife and husband's perception of household's level of poverty, wife and husband's error in the number of dependents, and alcohol consumption.

Chapter 4

Are Disaster Funds Enough to Smooth Consumption?

with Juan Enrique Huerta-Wong[1] *and Julieth Santamaria*[2 3]

4.1 Introduction

Natural disasters worldwide have increased considerably since the 1970s, affecting on average over 200 million people every year (Leaning and Guha-Sapir, 2013). Natural disasters may greatly reduce children's human capital accumulation by affecting prices, assets, and the consumption of families. Yet, the impact of natural disasters on consumption is widely debated. While economic theory predicts that individuals can maintain their levels of consumption against income shocks,[4] there is evidence that this is not always the case when facing a natural disaster (Kazianga and Udry, 2006).

What kind of public policies can be implemented to protect families' consumption

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[4]Under the assumptions that insurance and/or credit markets function well.

from a natural disaster? One possibility is through the use of insurance. In particular, governments can use disaster funds, i.e. save resources ex-ante for post-disaster use (De Janvry, Del Valle and Sadoulet, 2016) or use catastrophe (CAT) bonds to insure against the consequences of a natural disaster (Borensztein, Cavallo, and Jeanne, 2017). To the best of our knowledge, Mexico was the first developing country to use disaster funds and catastrophe bonds through the Fund for Natural Disasters (FONDEN). FONDEN resources are used to provide immediately supplies of food, medicines, cleaning supplies and toiletries to the households affected, and also provides resources for the reconstruction of housing and public infrastructure affected. De Janvry, et al. (2016) find evidence that FONDEN increases local economic activity between 2 and 4 percent in the year following the disaster. Thus, this program can be an important factor mitigating the effects of natural disasters in the medium term.

But, can FONDEN smooth the consumption of families affected by a natural disaster in the short term? To answer this question, we exploit the occurrence of Hurricane Earl, which had a large impact on the state of Puebla, Mexico, in 2016. This disaster happened unexpectedly in areas that do not usually experience hurricanes. Survey data were collected from municipalities within the state of Puebla that are comparable in terms of their ranking in the Human Development Index.[5] Huachinango and Tlaola are treatment municipalities (affected by the hurricane and received resources through the FONDEN) while Palmar de Bravo and Juan C. Bonilla are the comparison municipalities. We use a difference-in-differences estimation procedure to test the hypothesis that the use of FONDEN can protect families' consumption when they are affected by a hurricane. We find that the quantity consumed of key food items diminishes. In particular, of the 12 items analyzed, we observe a decrease in

[5]The Human Development Index is a composite statistic of life expectancy, education, and per-capita income, which is used to rank countries regarding human development.

the consumption of beans, lemons, sugar, beef, and chicken.

A large body of literature has analyzed the effects of negative income shocks on households' behavior. This literature was initially motivated by the neoclassical life cycle model, also known as the permanent income hypothesis, which suggests that individuals tend to smooth their consumption over their lifetime by saving when they have income surpluses and dis-saving during hard times (Modigliani and Brumberg, 1954). However, the literature has also found that precautionary saving is very rare, particularly for uneducated households and individuals in the lower tail of the income distribution (Bernheim and Scholz, 1993; Browning and Lusardi, 1996). After natural disasters occur, households react in different ways to smooth their consumption and recover from the loss. For example, families can choose to sell assets in order to smooth their consumption, or they may reduce their present consumption in order to keep their assets. Hoddinott (2006) finds evidence that poorer households tend to smooth their assets rather than smooth their consumption. Consistent with this, Fafchamps, Udry, and Czkas (1998) find that households in West Africa do not sell assets after a severe drought. Their hypothesis is that households choose to protect their productive investment because the low market price prevailing at the time of the sale would not compensate for the loss.

This paper contributes to the recent literature on the use of disasters funds, providing evidence that a natural disaster fund (FONDEN) is not always sufficient to protect families' consumption (at least in the short run). In addition, the results provide no evidence that the hurricane affected families differently depending on their wealth. These results imply the need to review the way in which FONDEN is operating:

i. It is necessary to analyze whether the quantity and periodicity with which food is distributed is the most appropriate. According to the Mexican government, about 2,196 families were affected by Hurricane Earl. The government reported that food baskets were distributed as follows: 1,200 in August 7th; 1,200 in August 11th; and 2,196 in August 26th. This reflects that not all the affected families were served and that the periodicity of delivery of food was not regular.

iii. It is important to establish mechanisms of accountability and transparency. The survey includes a question regarding whether families received help from natural disasters. Of the 327 families surveyed (14% of the total families affected), only 6 families reported receiving government support as a consequence of the natural disaster. Some possible explanations are: a) the families are underreporting the aid received from the government in order to continue receiving benefits; b) the families surveyed are part of the group that did not receive help from the government; or c) it is possible that these families did not receive support from the government. In order to know how the support is granted, it is necessary that FONDEN report a list of the families served. This will generate transparency and avoid possible situations of corruption in the delivery of food to the affected families.

The remainder of this paper proceeds as follows. First, we describe the geographical location and impact of Hurricane Earl on Puebla and we explain in more detail the FONDEN program. We then describe the data, present descriptive statistics, and explain the identification strategy. Finally, we describe the results and give some insights about their policy implications.

4.2 Background

Mexico is among the 30 countries that are most exposed to two types of natural disasters: hurricanes and earthquakes. The population that is most vulnerable to these natural disasters represents around 27% of the country (INEGI, 2013). A natural disaster can greatly reduce human capital accumulation and, as a consequence, decrease the possibility of social mobility. Its first effect is through income, which clearly has the potential to affect consumption and education. While economic theory predicts that individuals can maintain their levels of consumption against temporary income shocks, there is evidence that this is not always the case (Kazianga and Udry, 2006). On the other hand, other studies have found that natural disasters affect students' school attendance (Jensen 2000, Cameron and Worswick 2001). One consensus from these studies is that families who are affected most are less likely to have insurance coverage (formal or informal), and are relatively poor.

4.2.1 The Fund for Natural Disasters (FONDEN)

In response to the vulnerability of Mexico to natural disasters, the Mexican Government established the Fondo de Prevención de Desastres Naturales (Fund for Natural Disasters Prevention, FOPREDEN) and the Fondo de Desastres Naturales (Fund for Natural Disasters, FONDEN). FOPREDEN is a program intended to generate actions for the *prevention* and reduction of risks due to natural disasters. FONDEN is a financial instrument by which the Mexican government allocates resources ex-ante for post-disaster *immediate attention* to the population affected and for *reconstruction* of the damaged infrastructure. FONDEN is composed of two main instruments: the Emergency Relief Fund and the Reconstruction Program. The former serves the population immediately by supplying food, medicines, cleaning supplies and toiletries, and the latter provides resources for the reconstruction of affected housing and public infrastructure. For the fiscal year 2016, FOPREDEN received $358,718,014 pesos (US$19,928,778) and FONDEN received $8,035,987,256 pesos (US$446,443,736). If this funding is insufficient, additional resources can be transferred from other federal programs.

4.2.2 Hurricane Earl in Puebla

Hurricane Earl was the deadliest Atlantic Hurricane to hit Mexico since Hurricane Stan in 2005. It started on August 2 and dissipated on August 6 of 2016. According to media reports, 54 individuals died, of which 41 were from the state of Puebla. This number exceeds the 33 deaths for Mexico as a whole reported for all 10 hurricanes that occurred in 2014 and 2015. According to the Global Catastrophe Recap (2016), the damage associated with Earl is estimated to be US$132 million.

Given the gravity of the hurricane, the Mexican government declared a state of emergency in three municipalities of Puebla: Huachinango, Tlaola, and Xicotepec. According to information provided by the Mexican government, 8,784 individuals were affected (around 2,000 families). The government distributed "despensas" (a food basket containing sugar, rice, beans, oil, corn, coffee, cookies, tuna, sardines, among other supplies) as follows: 1,200 in August 7th, 1,200 in August 11th, and 2,196 in August 26th. The total cost spent on food was $1,603,382 pesos (US$ 89,076). Finally, according to the media, the Mexican government received US$200,000 from the Inter-American Development Bank to purchase food for the families affected.[6]

[6] In addition, the government spent: $764,208 pesos (US$42,456) on 8,784 blankets, $2,304,851 pesos (US$128,047) on 8,784 mats, $524,775 pesos (US$29,154) on 5,592 toiletries kits, $384,906 pesos (US$21,383) on 2,196 sets of cleaning supplies, $552,960 (US$30,720) on 76,800 bottles of water, and $8,836,211 pesos (US$490,900) on medicines.

4.3 Data

To analyze the effects of Hurricane Earl, we use a unique dataset that was collected in affected municipalities in Puebla after the disaster took place. The data are part of Mexico's Survey of Social Mobility in Disaster Zones (SSMDZ). The survey selects locations that were affected in the current year, but were not affected by a hurricane or other natural disaster in the previous four years. In addition, the survey includes a comparison group that was neither affected by the current natural disaster nor by any other natural disaster in the last four years. The comparison group should be located close to the affected area, and should have a Human Development Index that is similar to those of the affected municipalities before the natural disaster took place. The SSMDZ data contain information on two affected municipalities: Tlaola and Huauchinango. Data were also collected from two municipalities that are used as controls: Palmar de Bravo and Juan C. Bonilla.[7]

Table 4.1 displays descriptive statistics regarding the number of members in the household and the possession of assets. As mentioned before, the treatment and comparison groups were selected to ensure that the municipalities were as similar as possible in terms of their location and the Human Development Index. However, the table displays baseline differences between the treatment group and the comparison group. In particular, Table 4.1 shows that, previous to the shock, households in the comparison group tend to have more assets than households affected by the hurricane.

Regarding consumption and prices, the survey contains information about 12

[7]Puebla was founded on December 21, 1823 and consists of a total of 217 municipalities.

items: corn tortillas, beans, tomatoes, lemons, bananas, sugar, beef, chicken, eggs, milk, alcohol, and cigarettes. All individuals were asked the following question about consumption before the hurricane: did your household consume (item) in (month)? If the individuals answered yes, then they were asked information about the quantity consumed and the price. Finally, similar questions were asked of the individuals regarding consumption and prices after the hurricane. The hurricane affected the treatment group municipalities from August 2 to August 6, 2016. The survey was implemented in September 2016, and the respondents were also asked to recall information about prices and consumption from the month of July 2016.

The response rates regarding consumption and prices before the hurricane Earl are presented in first Column of Table 4.2. Regarding the question about consuming a particular product ("Did your household consume...?"), the percentage of households with no response (i.e. did not answer the question) ranges from 1.8% for sugar to 2.7% for beans. From those individuals who answered that they did consume such items, almost all the individuals responded with the quantity that they consumed (see Column 4 in Table 4.2).[8]

Table 4.3 presents the rates of consumption of these goods before the hurricane, separately for "treatment" and "control" municipalities, and we can observe impor-

[8]These high rates of response can be explained by important changes to the instrument used to collect the information. For example, a similar survey collected information in the aftermath of the Hurricane Odile, which affected the state of Baja California Sur. This hurricane affected that area between September 10 and September 24, 2014. The survey was implemented during June of 2015, and the people surveyed were asked to recall information regarding the month of August 2014. Of the people who answered positively consumption, almost half of them were not able to respond the quantity consumed. So, it is clear that the time period for which the people were asked to recall information matters. Another potential explanation could be the length of the questionnaire. In the case of the survey collected for Hurricane Earl, it was decided to shorten the questionnaire. For example, when the individuals surveyed answer the consumption module, they have were asked 153 questions in the case of the Hurricane Odile, but only 82 questions in the case of the Hurricane Earl.

tant differences in the patterns of consumption. For example, 75% of the households in the treatment localities reported consuming corn tortillas, compared to 91% for the control group. Another example is the consumption of alcohol, where 24% of the households in the treatment group reported consuming alcohol, while the percentage is only 14% in the control group. Table 4.4 presents the quantities[9] consumed in the treatment and control groups. Depending on the item, some goods are consumed more in the treatment group while others are consumed more in the control group. For example, the control group consumes an average of 6.98 kg of corn tortilla per week per household vs 4.32 kg in the treatment group; however, for sugar, the control group consumes 1.92 kg vs 2.57 kg in the treatment group. Finally, Table 4.5 presents information regarding prices. In general, the families in the treatment group report higher prices than those in the control group; yet, there are some exceptions, such as alcohol or cigarettes.

4.4 Empirical Strategy

The objective of this paper is to examine whether the FONDEN resources are sufficient to smooth the consumption of the families affected by the Hurricane Earl in Puebla, Mexico. Ideally, we would like to calculate the effects of the FONDEN on consumption by comparing the actual outcome with the outcome in the absence of the shock. Because this is impossible, we have to rely on the construction of a proper counterfactual. Since Hurricane Earl's trajectory was exogenous, households spared by the storm constitute a natural control group. Hence, the approach is to compare the changes in the outcome of interest in the localities directly hit by Hurricane Earl and where the FONDEN resources were used to the changes that occurred in the

[9] Unconditional on positive consumption.

control group localities.

We use a difference-in-differences (DID) approach to examine the effect on household consumption, assets, and prices:

$$Y_{it} = \beta_0 + \beta_1 After_t + \beta_2 Hurricane_i + \beta_3 \left(After_t * Hurricane_i\right) + X_i\theta_i + e_{it}$$

where Y_{it} is the outcome of interest for household i at time t. We look at various types of outcomes such as consumption and prices of a basket of goods that is relevant for the Mexican context; $After_t$ takes the value of 1 in the period after the shock; $Hurricane_i$ takes the value of 1 in the municipalities affected by the natural disaster and zero otherwise; X_i is a set of control variables. Notice that the coefficient of interest is β_3. It estimates the *combined* effect that the hurricane and the implementation of FONDEN have in the treated municipalities compared to the control group. More specifically, without FONDEN we expect $\beta_3 < 0$, but we want to see whether, with FONDEN, $\beta_3 = 0$. To identify the causal effect, the above difference-in-differences (DID) estimator must satisfies the following:

1. The additive structure imposed is correct.

2. $cov(e_{it}, After_t * Hurricane_i) = 0$.

The last assumption is known as the *parallel-trend* assumption, and it means that the outcome variables of the treatment and comparison groups followed the same trend over time before the hurricane took place. In other words, the unobserved characteristics that create a gap between measured treatment and control outcomes are assumed to be time invariant. Given that we only have two data points, we cannot test this hypothesis. However, these municipalities are located close to each other and they are all located in the State of Puebla. Therefore, we think that it is likely that in absence of the hurricane, the outcomes of interest for the four municipalities followed a similar trend.

Although a natural disaster is unexpected and non-manipulable by construction, the initial conditions of the families are likely to influence the subsequent consumption path. For example, it is possible that wealthy families recover faster from the hurricane using their savings or other assets to smooth their consumption. For this reason, we include an additional robustness check using a Kernel propensity matching technique combined with a DID. We use the predicted probability of being affected by the hurricane (the propensity score) to match the control municipalities. The propensity score is estimated using a probit model where the initial conditions are the assets holding of the families in the period before the hurricane. The average impact can be written as:

$$DD_i = (Y_{i2}^T - Yi1^T) - \sum_{j \in C} w(i,j)(Y_{j2}^C - Y_{j1}^C)$$

where w(i,j) is the weight using a Kernel matching in which all non-participants are used as comparison communes and weights are assigned according to a kernel function of the predicted propensity score.

Another potential source of endogeneity bias could be characteristics of the municipalities that might affect consumption outcomes. For example, economic opportunities might result in different consumption outcomes across the municipalities, even in the absence of the hurricane. Thus, as a robustness check, we will conduct a fixed effects regression at the municipality level.

4.5 Results

We analyze the effects on quantities consumed and prices of the following goods: corn tortillas, beans, tomatoes, lemons, bananas, sugar, beef, chicken, eggs, milk, alcohol, and cigarettes. Table 4.6, Column 3, presents estimates of the impact on consumption decisions (a *dummy* variable for the question "Did your household consume...?"). The estimates show that the hurricane affected negatively, and statistically significantly, the consumption of beans (-0.14), lemons (-0.06), sugar (-0.04), beef (-0.02) and chicken (-0.02). Column 5 presents the results regarding the quantities consumed, where significantly negative impacts are found only for beans (-.288). Regarding prices, they decrease for all the items analyzed except cigarettes, and these decreases are statistically significant for all items except sugar and milk (Column 7). In particular, a statistically significant decrease is observed in the prices of the following items: tortillas (-0.94 or 9.5%), beans (-1.91 or 7.3%), tomatoes (-3.52 or 26.3%), lemons (-1.68 or 14.5%), bananas (-1.33 or 13.8%), beef (-4.86 or 8.8%), chicken (-4.34 or 9.9%), and eggs (-1.09 or 5.8%).[10]

As a robustness check, we use a kernel propensity matching to identify a sample of households in the comparison group that had asset holdings similar to those of the households in the treatment group before the hurricane took place. Table B1 (Appendix) show the balancing test before and after the matching. There are many significant differences in asset holdings for the unmatched sample. This is also in line with the descriptive statistics provided in Table 4.1, which pointed out some differences between households in the treatment and the comparison groups. After the matching is implemented, most of the differences between the matched sample of the

[10]Finally a joint test was conducted for consumption, quantities consumed, and prices. We reject the null hypothesis that the effect of the hurricane on consumption and quantities consumed is not statistically significant at the 5 and 10 percent level, respectively. For prices, we reject the null hypothesis of no effect of the hurricane at the 5 percent level.

treatment and control groups are no longer significant. And even for those variables for which there are still differences such as DVD, water heater, cellphone, and piped water, there is a large reduction in the gap after the matching.

The results of the DID using the matched sample are displayed in Table 4.7. As compared to the basic specification in Table 4.6, the effects on consumption of beans, lemon, sugar, beef, and chicken remain significant and are even slightly larger. On quantities consumed, there is still a negative effect of the hurricane on the quantity consumed of beans, and we also find a negative and significant effect on the quantity of lemons. Finally, the effect of the hurricane on prices remains negative for most of the products except for sugar and milk, neither of which were significant in the basic specification. Thus, we find the same results even after implementing the propensity score matching.[11]

To confirm the results presented above regarding consumption and prices, we decided to use municipality fixed effects. The idea is to capture characteristics of the municipalities that might affect our variables of interest even in the absence of the Hurricane and the resources of FONDEN, such as the population of the villages, economic development, and institutional efforts to prevent natural disasters. Table 4.8 reproduces Table 4.6 using municipality fixed effects. We do not observe substantial changes with respect the results presented in Tables 4.6 and 4.7.[12]

[11] A joint test was conducted for consumption, quantities consumed, and prices. We reject the null hypothesis that the effect of the hurricane on consumption and quantities consumed is not statistically significant at the 5 and 10 percent level, respectively. For prices, we reject the null hypothesis of no effect of the hurricane at the 5 percent level.

[12] A joint test was conducted for consumption, quantities consumed, and prices. We reject the null hypothesis that the effect of the hurricane on consumption and quantities consumed is not statistically significant at the 5 and 10 percent level, respectively. For prices, we reject the null hypothesis of no effect of the hurricane at the 5 percent level.

It is possible that the changes in consumption reflect only substitution effects, so that it is possible that aggregate household consumption was not affected. To analyze this possibility, the consumption of the twelve items was aggregated, i.e. we generate a new variable, which adds the dummy variables regarding consumption, and which maximum value is twelve. The result is presented in Table 4.9, Column 1, and we still observe a decrease in consumption that is statistically significant (-0.302). Column 2 presents the aggregate consumption results that exclude alcohol and cigarettes. The results continue to be statistically significant, and a slight increase is observed (-0.314). Finally, column 3 presents the result when we add the quantities consumed excluding alcohol and cigarettes.[13] it is observed a decrease in the quantity consumed that is statistically significant (-0.581)

There is evidence that natural disasters can affect families differently depending on their levels of wealth (Carter and Lybbert, 2012). In order to verify this hypothesis, using the information regarding the sixteen assets captured in the survey, we generate an index of wealth using principal component analysis. This index goes from -3.16 (less assets) to 6.68 (more assets). Then we estimate the following model using difference-in-differences estimation:

$$Y_{it} = \beta_0 + \beta_1 After_t + \beta_2 Hurricane_i + \beta_3 Wealth_{0i} + \beta_4 After_t Hurricane_i + \beta_5 After_t Wealth_{0i} + \beta_6 Hurricane_i Wealth_{0i} + \beta_7 After_t Hurricane_i Wealth_{0i} + X_i \theta_i + e_{it}$$

where Y is the variable of interest (consumption); *After* is a dummy variable that takes the value of 1 after the shock; $Hurricane_i$ is a dummy variable that takes the value of 1 for the affected areas, and zero otherwise; $Wealth_{0i}$ is a variable that measures the wealth of the families before the hurricane; and X is a group of control variables. In this specification our coefficient of interest is β_7.

[13] For the case of milk, it is assumed that 1kg= 1 liter.

Table 4.10 presents results regarding the probability of consuming and the quantity consumed when the wealth of the families previous to the hurricane is taken into account. Column 3 presents the results when the consumption is analyzed. For the twelve items analyzed, we observe a statistically significant effect (0.029) only for the consumption of beef. Given that the sign of the effect is positive, it implies that households with low levels of assets were more affected. The results regarding the quantities consumed are presented in Column 5. In this case, the only coefficient that is statistically significant at the 10% level is associated with the consumption of chicken: -0.048. The negative sign of the effect implies that households with high level of assets were most affected. Finally, we conducted a joint test, and we were not able to reject the null hypothesis of no effect of different levels of wealth on consumption and quantities consumed. Thus, it appears that the original level of wealth did not affect the decrease observed in the households consumption, i.e. we do not find evidence of heterogeneity.

Although families received support from FONDEN and there was a drop in prices, these factors were not enough to smooth the consumption of households affected by the hurricane. In addition, we do not find evidence that the hurricane affected families differently depending on their wealth. Regarding the decrease observed in prices, it is possible a consequence of an important decrease in income that affected the demand for food. Yet, other potential hypotheses are plausible, such as, that markets are not well integrated or the families sold at a lower price the items included in the "despensa" (for example, it could be the case of products that families do not like), causing a drop in prices.

4.6 Conclusion

This paper analyzes the ability of a disaster fund program (FONDEN) to smooth the consumption of families affected by Hurricane Earl in Puebla, Mexico. In particular, the analysis examines quantities consumed and prices for the following goods: corn tortillas, beans, tomatoes, lemons, bananas, sugar, beef, chicken, eggs, milk, alcohol, and cigarettes. The results show a decrease in the consumption of five of the twelve goods analyzed, including beans, which is an essential staple good for Mexican families. In addition, estimates of the effect on prices are negative, but this decrease in prices was not enough to maintain the consumption of the families.

The Fund for Natural Disasters (FONDEN) program provides food to families affected and supports the reconstruction of the infrastructure in the affected areas. In addition, the Mexican Government received US$200,000 from the Inter-American Development Bank to purchase food for the affected families. Yet, our results indicate that this aid was not enough to protect the consumption of families who were affected. De Janvry, et al. (2016) find evidence that this program (FONDEN) increases local economic activity between 2 and 4 percent in the year following the disaster. Thus, this program can be an important factor mitigating the effects of natural disaster in the medium term. Yet, it is necessary that the program review whether the quantity, quality, and periodicity with which food is distributed are the most appropriate. Improving these factors potentially can help to smooth the consumption of families affected in the short term.

Table 4.1: Descriptive Statistics Assets: Puebla

Variables	Treatment	Control	Difference
Number of members of the HH	4.67	4.09	0.58***
Computer	0.02	0.28	−0.26***
Stove	0.44	0.95	−0.51***
Washing machine	0.04	0.54	−0.50***
Refrigerator	0.26	0.74	−0.48***
DVD	0.23	0.40	−0.17***
TV	0.55	0.89	−0.34***
Water heater	0.16	0.44	−0.28***
Cellphone	0.30	0.66	−0.36***
Microwave	0.02	0.20	−0.18***
Toaster	0.00	0.12	−0.12***
Internet	0.01	0.25	−0.24***
Piped water	0.85	0.56	0.29***
Toilet inside hh	0.71	0.86	−0.15***
Electricity	0.98	0.99	−0.01
Landline	0.21	0.32	−0.11***
Cable TV	0.17	0.22	−0.05*
Car	0.05	0.28	−0.23***
Number of observations	328	334	

Note: Tlaola and Huauchinango are treatment municipalities while Palmar de Bravo and Juan C. Bonilla form the comparison group. Clustered standard errors at the street level.

Source: Survey of Social Mobility in Disaster Zones.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.2: Percentage of Pre-Hurricane Responses Regarding Consumption (Puebla)

	Did your household consume...? No answer (%)	No (%)	Yes (%)	How much...? Answer (%)
Corn tortilla	1.9	8.5	89.5	100.0
Bean	2.7	10.9	86.3	100.0
Tomato	1.8	1.6	96.5	100.0
Lemon	2.5	23.3	74.1	99.6
Banana	2.3	19.0	78.7	100.0
Sugar	1.8	3.4	94.8	99.7
Beef	2.1	24.4	73.5	99.6
Chicken	1.9	7.9	90.1	99.8
Eggs	2.1	10.9	86.9	99.7
Milk	2.3	28.4	69.3	99.8
Alcohol	1.9	90.9	7.2	93.8
Cigarettes	1.9	95.4	2.7	100.0

Note: Data combined for treatment and control group.

*** p <0.01, ** p <0.05, *p <0.1

Table 4.3: Descriptive Statistics Consumption: Puebla (Pre-Hurricane)

Variables	Treatment	Control	Difference
Corn tortilla	0.75	0.91	−0.16***
Bean	0.89	0.88	0.01
Tomato	0.99	0.98	−0.01
Lemon	0.63	0.75	−0.12***
Banana	0.90	0.80	0.10***
Sugar	0.99	0.96	0.03**
Beef	0.96	0.75	0.21***
Chicken	0.96	0.91	0.04***
Eggs	0.92	0.88	0.04**
Milk	0.70	0.69	0.01
Alcohol	0.24	0.14	0.10***
Cigarettes	0.01	0.03	0.02**

Note: Tlaola and Huauchinango are treatment municipalities while Palmar de Bravo and Juan C. Bonilla form the comparison group. Clustered standard errors at the street level.

Source: Survey of Social Mobility in Disaster Zones

*** p<0.01, ** p<0.05, * p<0.1

Table 4.4: Descriptive Statistics Quantities Consumed per Household: Puebla (Pre-Hurricane)

Variables	Treatment	Control	Difference
Corn tortilla	4.32	6.98	−2.66***
Bean	1.40	1.83	−0.43***
Tomato	1.87	2.84	−0.97***
Lemon	0.71	1.29	−0.58***
Banana	2.02	1.75	0.27**
Sugar	2.57	1.92	0.65***
Beef	1.09	1.09	0.00
Chicken	1.20	1.59	−0.39***
Eggs	1.16	1.41	−0.25**
Milk	1.54	3.76	−2.21***
Alcohol	0.16	0.08	0.08***
Cigarettes	0.01	0.06	−0.05**

Note: Tlaola and Huauchinango are treatment municipalities while Palmar de Bravo and Juan C. Bonilla form the comparison group. Clustered standard errors at the street level.

Source: Survey of Social Mobility in Disaster Zones

*** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Descriptive Statistics Prices: Puebla (Pre-Hurricane)

Variables	Treatment	Control	Difference
Corn tortilla	9.89	8.99	0.90***
Bean	25.91	19.37	6.54***
Tomato	13.32	10.71	2.61***
Lemon	11.47	9.10	2.37***
Banana	9.59	8.31	1.27***
Sugar	19.04	14.08	4.95**
Beef	54.74	66.87	−12.13***
Chicken	43.70	43.10	0.59
Eggs	18.92	20.78	−1.85**
Milk	13.08	11.00	2.08***
Alcohol	9.06	15.83	−6.77***
Cigarettes	31.50	44.63	−13.13*

Note: Chicahuaxtla (Tlaola) and Xaltepec (Huauchinango) are treatment municipalities while Palmar de Bravo and Juan C. Bonilla form the comparison group. Clustered standard errors at the street level.

Source: Survey of Social Mobility in Disaster Zones.

*** p<0.01, ** p<0.05, * p<0.1

Table 4.6: Difference-in-Difference Estimates of the Impact of the Hurricane on Food Consumption and Prices

	Consumption		Quantity		Price	
Variables	Mean	Estimate	Mean	Quantity	Mean	Price
Tortillas	0.739	−0.003	4.752	−0.030	9.908	−0.944***
	0.439	(0.005)	5.323	(0.068)	0.871	(0.104)
Beans	0.902	−0.140***	1.514	−0.288***	25.927	−1.911***
	0.298	(0.023)	2.129	(0.099)	9.041	(0.523)
Tomatoes	0.995	−0.003	2.098	−0.009	13.374	−3.520***
	0.068	(0.005)	1.771	(0.041)	4.388	(0.435)
Lemon	0.650	−0.056***	0.770	−0.068	11.574	−1.689***
	0.477	(0.018)	1.006	(0.044)	6.367	(0.432)
Plantain	0.917	−0.020	2.096	−0.075	9.572	−1.336***
	0.275	(0.013)	1.310	(0.056)	3.496	(0.330)
Sugar	0.996	−0.040**	2.776	−0.183	18.959	−0.533
	0.063	(0.017)	2.564	(0.130)	8.075	(0.404)
Alcohol	0.240	0.011	0.164	−0.009	9.247	−12.739*
	0.427	(0.030)	0.384	(0.028)	7.496	(6.748)
Cigarretts	0.005	0.006	0.005	0.006	31.500	15.636**
	0.072	(0.008)	0.072	(0.031)	6.949	(5.661)
Beef	0.974	−0.023**	1.141	0.023	55.195	−4.867***
	0.160	(0.012)	0.568	(0.032)	11.519	(0.901)
Chicken	0.974	−0.018**	1.254	0.025	43.832	−4.340***
	0.158	(0.009)	0.646	(0.031)	6.734	(0.606)
Eggs	0.951	−0.003	1.276	−0.025	18.917	−1.098***
	0.216	(0.017)	1.023	(0.034)	5.362	(0.339)
Milk	0.707	−0.001	1.664	−0.028	13.262	−0.173
	0.455	(0.013)	1.901	(0.069)	6.703	(0.198)

Note: Clustered standard errors displayed in parenthesis at the street level. The table displays for each outcome the mean outcome for the treatment group before the hurricane, and the interaction term between the treatment and the after dummy. The sample size for consumption ranges from 1,291 for milk to 1,307 for tortillas. In the case of the quantities, it ranges from 1,287 for alcohol to 1,308 for tomatoes. Finally, in the case of prices, it ranges from 889 for lemons to 1,306 for beef, with the exceptions of alcohol (164) and cigarettes (22).
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Matching Difference-in-Difference Estimates of the Impact of the Hurricane on Food Consumption and Prices

	Consumption		Quantity		Price	
Variables	Mean	Estimate	Mean	Quantity	Mean	Price
Tortillas	0.739	−0.008	4.752	−0.067	9.908	−0.852***
	0.439	(0.009)	5.323	(0.092)	0.871	(0.106)
Beans	0.902	−0.153***	1.514	−0.298**	25.927	−1.355**
	0.298	(0.027)	2.129	(0.124)	9.041	(0.562)
Tomatoes	0.995	−0.002	2.098	−0.016	13.374	−3.139***
	0.068	(0.007)	1.771	(0.043)	4.388	(0.541)
Lemon	0.650	−0.058***	0.770	−0.094**	11.574	−0.932**
	0.477	(0.015)	1.006	(0.039)	6.367	(0.446)
Plantain	0.917	−0.025	2.096	−0.063	9.572	−1.016***
	0.275	(0.015)	1.310	(0.051)	3.496	(0.376)
Sugar	0.996	−0.044***	2.776	−0.219	18.959	−0.022
	0.063	(0.016)	2.564	(0.144)	8.075	(0.487)
Alcohol	0.240	−0.005	0.164	−0.004	9.247	−10.081*
	0.427	(0.031)	0.384	(0.028)	7.496	(5.266)
Cigarretts	0.005	0.010	0.005	0.015	31.500	20.836***
	0.072	(0.009)	0.072	(0.012)	6.949	(6.495)
Beef	0.974	−0.032**	1.141	0.004	55.195	−4.311***
	0.160	(0.015)	0.568	(0.031)	11.519	(1.270)
Chicken	0.974	−0.023**	1.254	0.016	43.832	−4.169***
	0.158	(0.011)	0.646	(0.034)	6.734	(0.740)
Eggs	0.951	−0.008	1.276	−0.010	18.917	−1.596***
	0.216	(0.014)	1.023	(0.037)	5.362	(0.496)
Milk	0.707	−0.009	1.664	−0.039	13.262	0.006
	0.455	(0.013)	1.901	(0.085)	6.703	(0.284)

Note: Clustered standard errors displayed in parenthesis. The table displays for each outcome the mean outcome for the treatment group before the hurricane, and the interaction term between the treatment and the after dummy. The difference-in-differences estimator include fixed effects at the street level. The sample size for consumption ranges from 1,291 for milk to 1,307 for tortillas. In the case of the quantities, it ranges from 1,287 for alcohol to 1,308 for tomatoes. Finally, in the case of prices, it ranges from 889 for lemons to 1,306 for beef, with the exceptions of alcohol (164) and cigarettes (22).
*** p<0.01, ** p<0.05, * p<0.1

Table 4.8: Municipality Fixed Effect Estimates of the Impact of the Hurricane on Food Consumption and Prices

	Consumption		Quantity		Price	
Variables	Mean	Estimate	Mean	Quantity	Mean	Price
Tortillas	0.739	−0.003	4.752	−0.032	9.908	−0.944***
	0.439	(0.005)	5.323	(0.068)	0.871	(0.105)
Beans	0.902	−0.140***	1.514	−0.293***	25.927	−2.080***
	0.298	(0.023)	2.129	(0.099)	9.041	(0.496)
Tomatoes	0.995	−0.003	2.098	−0.009	13.374	−3.531***
	0.068	(0.005)	1.771	(0.041)	4.388	(0.436)
Lemon	0.650	−0.057***	0.770	−0.068	11.574	−1.742***
	0.477	(0.018)	1.006	(0.045)	6.367	(0.434)
Plantain	0.917	−0.020	2.096	−0.073	9.572	−1.331***
	0.275	(0.013)	1.310	(0.056)	3.496	(0.329)
Sugar	0.996	−0.040**	2.776	−0.185	18.959	−0.483
	0.063	(0.017)	2.564	(0.131)	8.075	(0.401)
Alcohol	0.240	0.011	0.164	−0.009	9.247	−12.264*
	0.427	(0.031)	0.384	(0.028)	7.496	(6.674)
Cigarretts	0.005	0.006	0.005	0.006	31.500	15.804**
	0.072	(0.008)	0.072	(0.031)	6.949	(5.871)
Beef	0.974	−0.024**	1.141	0.022	55.195	−4.837***
	0.160	(0.012)	0.568	(0.032)	11.519	(0.898)
Chicken	0.974	−0.018**	1.254	0.025	43.832	−4.336***
	0.158	(0.009)	0.646	(0.031)	6.734	(0.603)
Eggs	0.951	−0.002	1.276	−0.024	18.917	−1.096***
	0.216	(0.017)	1.023	(0.034)	5.362	(0.339)
Milk	0.707	−0.003	1.664	−0.030	13.262	−0.170
	0.455	(0.013)	1.901	(0.071)	6.703	(0.196)

Note: Clustered standard errors displayed in parenthesis at the street level. The table displays for each outcome the mean outcome for the treatment group before the hurricane, and the interaction term between the treatment and the after dummy. The estimator include fixed effects at the municipality level. The sample size for consumption ranges from 1,291 for milk to 1,307 for tortillas. In the case of the quantities, it ranges from 1,287 for alcohol to 1,308 for tomatoes. Finally, in the case of prices, it ranges from 889 for lemons to 1,306 for beef, with the exceptions of alcohol (164) and cigarettes (22).
*** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Difference-in-Difference Estimates on Aggregated Consumption

Variables	(1) Total Consumption	(2) Consumption w/o Alcohol and Cigarettes	(3) Quantity w/o Alcohol and Cigarettes
After	-0.153***	-0.021	-0.164
	(0.044)	(0.034)	(0.138)
Treatment	0.705*	0.562	-6.275***
	(0.401)	(0.363)	(0.996)
After*Treatment	-0.302***	-0.314***	-0.581**
	(0.071)	(0.063)	(0.264)
Constant	9.576***	9.510***	24.049***
	(0.022)	(0.017)	(0.780)
Observations	1,324	1,324	1,324
R-squared	0.184	0.187	0.075

Note: Clustered standard errors displayed in parenthesis at the street level. For the case of milk, it is assumed that 1kg= 1 liter.
*** p<0.01, ** p<0.05, * p<0.1

Table 4.10: Heterogenous Estimates on Food Consumption

	Consumption		Quantity	
Variables	Mean	Estimate	Mean	Quantity
Tortillas	0.748	0.032	4.322	0.013
	0.435	(0.021)	4.980	(0.181)
Beans	0.899	0.014	1.401	0.033
	0.302	(0.025)	2.024	(0.056)
Tomatoes	0.994	0.003	1.873	−0.053
	0.078	(0.004)	1.524	(0.047)
Lemon	0.635	−0.034	0.710	0.036
	0.482	(0.021)	0.908	(0.037)
Plantain	0.908	0.019	2.029	−0.056
	0.290	(0.013)	1.317	(0.050)
Sugar	0.994	0.016	2.571	0.065
	0.078	(0.014)	2.365	(0.046)
Alcohol	0.240	−0.010	0.162	−0.029
	0.428	(0.018)	0.381	(0.025)
Cigarrettes	0.006	−0.006	0.006	−0.026
	0.078	(0.004)	0.078	(0.021)
Beef	0.966	0.029**	1.097	−0.002
	0.181	(0.012)	0.577	(0.047)
Chicken	0.966	0.005	1.200	−0.048*
	0.181	(0.009)	0.640	(0.029)
Eggs	0.929	0.009	1.164	−0.035
	0.256	(0.013)	0.908	(0.028)
Milk	0.693	−0.003	1.548	−0.072
	0.462	(0.019)	1.792	(0.079)

Note: Clustered standard errors displayed in parenthesis at the street level. The table displays for each outcome the mean outcome for the treatment group before the hurricane, and the interaction term between the treatment, the after dummy, and index of wealth. The sample size for consumption ranges from 1,291 for milk to 1,307 for tortillas. In the case of the quantities, it ranges from 1,287 for alcohol to 1,308 for tomatoes. *** p<0.01, ** p<0.05, * p<0.1

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Appendix A

Appendix Chapter 2

Table A1: Latent Variable Scales

Scale Name	Scale Survey Question	Factor Loadings
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
Authoritative Parents	[1] My parents make show me how much they love me	0.4651
Eigenvalue: 2.8	[2] My parents explain to me the consequences of my misconduct	0.4444
	[3] My parents encourage me to say what I feel when I disagree	0.4443
	[4] My parents reason with me when I misbehave	0.4441
	[5] My parents know my concerns	0.4400
Family Support	[1] My family recognizes what I do well	0.4295
Eigenvalue: 3.5	[2] My family really tries to help me	0.4593
	[3] My family helps me make decisions	0.4449
	[4] My family supports me when I need them	0.4648
	[5] My family is affectionate with me	0.4365

Table A2: OLS Estimates: Effects of Bullying on whether Adolescents Dropped Out of School

	(OLS)	(Probit)	(Logit)
Dep Var: Dropping Out			
Bullying	0.049***	0.214***	0.391***
	(0.012)	(0.054)	(0.094)
Father died	0.205***	0.681***	1.158***
	(0.062)	(0.257)	(0.444)
Mother died	0.173	0.818*	1.531*
	(0.107)	(0.469)	(0.794)
Parent in Prison	0.003	0.029	0.040
	(0.057)	(0.290)	(0.521)
Sex (Female=1)	-0.015	-0.060	-0.063
	(0.023)	(0.123)	(0.221)
Siblings	0.029***	0.134***	0.247***
	(0.007)	(0.036)	(0.065)
Siblings Older	-0.004	-0.016	-0.028
	(0.007)	(0.035)	(0.061)
Age	0.464	4.557**	9.713***
	(0.329)	(1.840)	(3.442)
Age squared	-0.014	-0.143**	-0.308***
	(0.011)	(0.063)	(0.117)
Constant	-3.816	-37.389***	-78.509***
	(2.377)	(13.451)	(25.256)
Municipality Fixed Effects	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses.

Appendix B

Appendix Chapter 4

Table B1: Balancing Test Before and After the Matching

Covariates		Treatment	Control	$p > \|t\|$
Computer	Unmatched	0.018	0.281	0.000
	Matched	0.018	0.019	0.933
Stove	Unmatched	0.443	0.949	0.000
	Matched	0.442	0.391	0.193
Washing machine	Unmatched	0.043	0.536	0.000
	Matched	0.043	0.050	0.655
Refrigerator	Unmatched	0.257	0.740	0.000
	Matched	0.258	0.241	0.631
DVD	Unmatched	0.232	0.401	0.000
	Matched	0.233	0.137	0.002
TV	Unmatched	0.554	0.892	0.000
	Matched	0.555	0.605	0.202
Water heater	Unmatched	0.162	0.443	0.000
	Matched	0.163	0.257	0.003
Cellphone	Unmatched	0.303	0.665	0.000
	Matched	0.304	0.232	0.037
Microwave	Unmatched	0.024	0.201	0.000
	Matched	0.025	0.019	0.656
Toaster	Unmatched	0.003	0.120	0.000
	Matched	0.003	0.005	0.731
Internet	Unmatched	0.009	0.251	0.000
	Matched	0.009	0.007	0.749
Piped water	Unmatched	0.847	0.563	0.000
	Matched	0.847	0.797	0.097
Toilet inside hh	Unmatched	0.713	0.862	0.000
	Matched	0.712	0.809	0.004
Electricity	Unmatched	0.982	0.988	0.503
	Matched	0.982	0.979	0.803
Landline	Unmatched	0.208	0.320	0.001
	Matched	0.209	0.141	0.023
Cable TV	Unmatched	0.168	0.225	0.069
	Matched	0.169	0.214	0.138