School Gun Violence, Mental Health, and Labor Outcomes Among Fragile Families and Disadvantaged Communities in the United States

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Dedication

I dedicate this research to all those who are waiting on the fulfillment of a promise from the Lord. "And the Lord visited Sarah as he had said, and the Lord did unto Sarah as he had spoken." Genesis 21:1 *King James Version*

Acknowledgment

This research could not have been performed without the encouragement, prayers, support, and guidance of many individuals. First and foremost, I would like to thank Jesus Christ for giving me strength throughout all the challenging moments of completing this research. I would like to extend my gratitude to Dr. Maya Rossin-Slater for allowing me to glean from her expertise and insight. I would also like to extend my appreciation to my dissertation advisor, Dr. Charlie Baum, for answering all of my questions whether small or large. I thank Dr. Aaron Gamino for his direction and assistance in acquiring the restricted FFCWS data. I extend my appreciation to Dr. Schuster for serving on my dissertation committee. I offer a special thank you to the donors of Middle Tennessee State University that provided funding for the purchase of the restricted data used in this research.

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Chapter 1

The Invisible Costs of School Shootings: Impacts on Parents' Mental Health and Children's Education Expectations

Chapter Abstract

Hundreds of thousands of US children have experienced gun violence at their schools in the last two decades. While prior research has analyzed the impacts of school shootings on children's outcomes, much less is known about how parents fare in the aftermath of gun violence at schools or how children's expectations regarding their educational trajectories are affected. I study the causal effects of school shootings on parents and children using data from the Fragile Families and Child Well-Being Study, leveraging variation in the timing of school shootings in parents' cities of residence relative to their randomly assigned survey interview dates. I find that school shootings adversely affect the mental health of parents of school-aged children. Specifically, I find that the mental health index of mothers is 0.100 standard deviations lower following exposure to a school shooting. Heterogeneity analyses also reveal that the mental health impacts on parents are concentrated among families with

married parents. Finally, I find that children's exposure to a school shooting negatively impacts their expectations regarding educational attainment. These results suggest that the costs of school shootings extend far beyond the direct impacts on victims who are killed or physically injured.[1]

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1.1 INTRODUCTION

Over 300,000 children have been exposed to school gun violence since the Columbine High School shooting in 1999 (Cox *et al.,* 2022). Research shows that these traumatic events have negatively affected children (Rossin-Slater *et al.,* 2020; Cabral *et al.,* 2020; Deb & Gangaram, 2021; Beland & Kim, 2016; Lacoe, 2020). But little is known about the impact of school shootings on parents. Moreover, while researchers have considered the impacts of gun violence at schools on children's educational trajectories over the long-run (Cabral *et al.,* 2020), we do not know whether these impacts might in part be shaped by changes in children's expectations regarding their education in the aftermath of a shooting. This paper fills these gaps in literature by analyzing the effects of school shootings on parental well-being and mental health, as well as children's expectations about their education.

Parents may be affected by school shootings through multiple mechanisms. First, schools are meant to be safe spaces for children to learn, but school shootings may disrupt this perception for parents. Consequently, parents become concerned for the safety of their children and may experience fear and stress when sending their children to school (Backus *et al.,* 2022). Second, along with their children, parents within communities exposed to a school shooting are left to cope with the aftermath and process the shock of their exposure. Though parents are aware of the possibility of school gun violence, no one can prepare for the impact of such an event (Figley & Kiser, 2013; Fromm, 2012; Beckerman & Henshaw, 2020). Third, because parents are the primary source of support for their children, after a school shooting, parents may neglect their own mental health needs due to time and financial constraints. Untreated mental illness can inhibit positive parenting and increase the likelihood of children developing mental illness (Steinberg, 1998; Briggs-Gowan *et al.,* 2010).[2]

Prior research has analyzed the effects of school shootings on the mental health, risky behaviors, and educational and economic outcomes of exposed children (Cabral *et al.,* 2020;

[2]Literature also shows that mental health issues diminish an individual's ability to work (LayaRd, 2017).

Rossin-Slater *et al.,* 2020; Deb & Gangaram, 2021; Levine & McKnight, 2021). Additionally, researchers have examined the impacts on children of gun violence in settings outside of schools (e.g. summer camp, neighborhood, and community violence) (Bharadwaj *et al.,* 2021; Aizer, 2008; R. Brown & Velásquez, 2017; Gershenson & Tekin, 2018), and a few studies have estimated effects on parents as well (Leibbrand *et al.,* 2021; Huang *et al.,* 2018; Bharadwaj *et al.,* 2021). Research indicates that parents have an increased likelihood of developing symptoms of depression, anxiety, and posttraumatic stress disorder (PTSD) stemming from their child's experience of maltreatment, abuse, or traumatic exposure. However, to date, there is scant evidence on how shootings at schools affect parents of school-aged children. This gap in the literature is important because children's psychological responsivity to violence is influenced by the parental response (Shaw, 2000; Appleyard & Osofsky, 2003). Healthy parental response to traumatic stressors—sensitivity to child's distress and support—help mitigate the risk of adverse psychological occurrences within children, but poor parental response—apathy and emotional detachment from the child—is a deterrent to children's recovery and coping ability (Shaw, 2000; Williamson *et al.,* 2016; Wise & Delahanty, 2017). Parents' poor mental health is likely to influence how they respond to their child's experience, further compounding the issues faced by the family (Dyb *et al.,* 2003; Holt *et al.,* 2017; Slaven-Lee *et al.,* 2011).

Gun violence in schools may similarly challenge children's perception of school as a safe place and thus hinder learning (Alisic *et al.,* 2011; Bassuk *et al.,* 2006). Several studies have linked trauma to adverse educational outcomes of children (Jackson *et al.,* 2022; Romano *et al.,* 2015; Ryan *et al.,* 2018). Both Levine and McKnight (2021) and Cabral *et al.* (2020) find that children exposed to school shootings exhibit decreases in academic performance and educational attainment. Furthermore, children exposed to trauma are more likely to have a pessimistic view of the world and life (Alisic *et al.,* 2011; Dyregrov *et al.,* 2002), potentially dampening their expectations about achieving higher education. However, to date, researchers have not considered whether exposure to trauma, more specifically school

gun violence, depresses children's educational expectations. This connection could have societal implications becuase prior research shows that children's educational attainment is positively correlated with their employment and wages as adults (Angrist & Keueger, 1991; Ashenfelter & Krueger, 1994). Accordingly, if children exposed to school shootings have lower educational expectations, they will be less likely to pursue higher education after high school, leading to lower wages.

Research on this topic has been limited because of two key barriers. First, few data sets contain information on (a) parents and their children, (b) their residence location at a finer level than the state, and (c) detailed mental health outcomes and family expectations. Second, exposure to gun violence is not randomly assigned, making it difficult to separate the causal effects of exposure to shootings from other differences between families. I overcome these barriers by using data from the Fragile Families and Child Wellbeing Study (FFCWS), which has been following nearly 5,000 families in large U.S. cities for 22 years and contains detailed information on a range of parental mental health and other related outcomes, such as the educational expectations of their children. The survey researchers intentionally over-sampled disadvantaged Black, Hispanic, and other low-income families, who are most likely to be exposed to gun violence at schools, and crime-related violence (Levine & McKnight, 2020).

For identification, I leverage the quasi-random variation in the timing of school shootings relative to interviews dates among families living within the same city. Using city-by-wave fixed effects, the impact of a school shooting within a wave is identified by comparing differences in parents' mental health and children's educational expectation outcomes among parents and children living within the same city who were interviewed at different times.

My results show that school shootings lead to a negative but insignificant decline in the overall mental health index of mothers, which encompasses a variable measuring the likelihood of experiencing a depressive episode and the parent's rating of life satisfaction.

However, this average masks important heterogeneity. When I split the sample by marital status I find that the mental health index of married mothers is 0.100 standard deviations lower following exposure to a school shooting.[3] Also, shooting-exposed children rate the importance of graduating from college 3 percentage points lower than children whom are not exposed.

This paper makes three primary contributions to the literature. First, prior research has explored the effects of school shooting exposure on children (Cabral *et al.,* 2020; Beland & Kim, 2016; Deb & Gangaram, 2021; Levine & McKnight, 2020; Levine & McKnight, 2021; Rossin-Slater *et al.,* 2020). These effects include poorer mental health, declines in standardized test scores and school attendance, and increased grade retention (Rossin-Slater *et al.,* 2020; Beland & Kim, 2016; Deb & Gangaram, 2021). Another complementary study shows that in the wake of a mass shooting at a summer camp in Utøya, Norway, surviving children saw significant increases in mental health diagnoses as did the parents of these children (Bharadwaj *et al.,* 2021). Although the results of previous studies suggest that the family unit, not only the children, could be affected by shooting exposure, my research is the first to specifically investigate the impact of school shooting exposure on parental mental health in the US setting. Second, researchers have found that the effects of school shooting exposure continue beyond the short run. Exposed children are less likely to graduate from high school and college, and in adulthood, have lower annual earnings than adults who were not exposed to school shootings as children (Cabral *et al.,* 2020; Deb & Gangaram, 2021). I extend this literature by analyzing whether changes in the likelihood of, or valuation of, graduating from college in the aftermath of a school shooting might be contributing to the previously documented changes in long-term educational outcomes among shooting-exposed children. Third, the unique FFCWS individual-level data set has been used by

[3]Few studies have investigated whether single and married mothers respond differently to negative non-recurring life events such as physical assault, financial crisis, or miscarriage, but researchers have found that recent negative life events have a greater positive correlation with depression among married mothers than among single mothers (Cairney, Thorpe, *et al.,* 1999; Cairney, Boyle, *et al.,* 2003).

many researchers to study factors affecting disadvantaged families, including violence and crime (Goetschius *et al.,* 2021; Leibbrand *et al.,* 2021). School shooting exposure is likely to compound the issues faced by these families. However, to the best of my knowledge, no prior study has used this data set to examine school shootings. My research captures the distinct impacts of exposure to school shootings on disadvantaged families rather than a broader effect of violence in the local community.

Understanding how school shootings affect families is critical to public policy debates. Parents constitute an important voting bloc, and several prominent grassroots initiatives have been organized by parents of affected children in response to school shootings.[4] In addition, expanding knowledge on how parents are impacted by school shootings can inform policies designed to curb gun violence, especially at schools. As evidenced by Levine and McKnight (2017), parents may respond to school shootings by purchasing guns, seeking to protect their families. However, this response is linked to increases in unintentional shootings of adults and children (Levine & McKnight, 2017). To date, research on the impacts of school shootings in the U.S. has focused almost exclusively on children, which could cause inefficiencies in policies created to encourage or curb event effects on children. One objective of this research is to document some of the ways school shootings affect both parents and children to help shed light on the types of supports communities may need in the aftermath of a shooting (i.e., mental health treatment for parents and children).

The remainder of this paper is organized as follows: Section 1.2 discusses the data. Section 1.3 introduces the empirical specification. Section 1.4 presents the results and robustness checks. Lastly, section 1.5 concludes.

[4]Examples of grassroots movements that seek to influence gun laws are "Moms Demand Action," (https://momsdemandaction.org/) and "Everytown," (https://www.everytown.org/).

1.2 DATA

I use two sources of data for my analysis: data on the locations and dates of school shootings, and survey data capturing outcomes in families. I describe these data sources in more detail below.

1.2.1 School Shooting Data

The Center for Homeland Defense and Security's K-12 School Shooting Database (CHDS) provides detailed information on school shootings from 1970 to the present. Using location as the primary qualifier to differentiate a 'shooting' from a 'school shooting', CHDS defines a school shooting as an event in which "a gun is brandished, is fired, or a bullet hits school property for any reason, regardless of the number of victims, time, day of the week, or reason" (Riedman & O'Neill, n.d.). The CHDS contains detailed information about each shooting, including news source(s), level of media attention, the reliability of source, date, quarter, city, school, location, time shooting took place, summary, and a narrative description of the event. CHDS gathers information on school shootings from multiple original sources: news articles, websites, newspapers, blogs, government reports, the Department of Education, and mainstream media. These sources are cross referenced and checked for their validity.

To capture the effects of shootings that likely affect many students, I only consider shootings that occurred during school hours. There were 81 school shootings that occurred between February 1998 and March 2017 in the 20 cities represented by the Fragile Families and Child Wellbeing Study. Fifty-one of the eighty-one occurrences took place during school and are the school shootings considered for the analysis.

Over my analytic time frame, twenty-six of the shootings took place in Chicago, Detroit, and Jacksonville; 10, 9, and 7, respectively. All other cities experienced 4 or less during this period. The maximum number of shootings experienced in any wave is 5. Six cities

experienced no school shootings between February 1998 and March 2017: Toledo, Boston, Corpus Christi, Norfolk, Richmond, and San Jose. In Figure 1.1, I illustrate the total number of school shootings by city between February 1998-March 2017.[5] Apart from two cases, school shootings within the study were not "headlined" on national media outlets.[6] Most were reported only by news media within the city's local area. Twelve of the 51 school shootings caused fatalities.[7] Only one shooting led to more than one death (2), which took place in Jacksonville in 2012. Sixty-five percent (33) of the shootings yielded nonfatal injures, the remaining 12% had no physical injuries. I show in Figure 1.2 that over 50% of the sample of school shootings used in this study are identified as an "escalation of dispute."[8] Suicide and attempted suicides account for the least number of school shooting situations (3).

1.2.2 Fragile Families Child Wellbeing Study

I use the restricted-use version of the Fragile Families and Child Wellbeing Study (FFCWS) which is a longitudinal panel data set, that has been following 4,898 families since the births of the focal child; in years 1998-2000. Since then, the families were surveyed over the course of 6 waves, when their children are approximately 1, 3, 5, 9, and 15 years old. Each child's mother and father were surveyed separately in waves 1 through 5, while in wave 6, only the child's primary caregiver was surveyed. The survey sampled families with children born in 20 metropolitan cities in the United States, oversampling couples who were unmarried at the time of childbirth. The twenty cities included in the FFCWS are Austin, TX, Baltimore, MD, Boston, MA, Chicago, IL, Corpus Christi, TX, Detroit, MI, Indianapolis, IN, Jacksonville, FL, Milwaukee, WI, Nashville, TN, New York, NY, Newark, NJ, Norfolk, VA, Oakland, CA, Philadelphia, PA, Pittsburgh, PA, Richmond, VA, San Antonio, TX, San Jose, CA, and

[5] New York, Richmond, San Jose, Indianapolis, and Philadelphia experienced a school shooting in January 1999, June 1998, September 1999, December 1998, and November 1998, respectively; but these school shootings occurred prior to the cities' baseline interview.

[6] The school shooting in Austin, TX received national media attention and a school shooting dated March 6, 2012 in Jacksonville, FL received international media attention.

[7] Two deaths were due to self-harm.

[8] Escalation of dispute refers to two parties previously involved in a confrontation, now engaging in a heightened situation.

Toledo, OH.[9] The restricted-use version contains geographic identifiers, as well as data on crime rates in each city and wave, which I use for my analysis (as described below).

From 1998 to 2000, families were chosen randomly at birthing hospitals in each city to participate in the Fragile Families Study. In most cases, mothers were interviewed within 48 hours of giving birth; fathers were interviewed within 2 weeks. The FFCWS contains data on parenting, health, relationships, finances, expectations, and demographics. The oversampling of unwed families in metropolitan cities makes this data ideal for this study because data are collected on nonresident fathers, "a group that past research had found elusive" (M. Brown, 2014).[10]

The analytic sample is limited to parents which participated in the baseline interview. Parents' city of residence is identified in the baseline interview, wave 1. If parents join the survey in subsequent waves, their city of residence is not disclosed which prohibits the identification of school shooting exposure for these parents. For this reason, one mother and 1,068 fathers are dropped from the sample which leaves 4,897 mothers and 3,830 fathers. I further limit the sample by dropping parents that did not participate in the FFCWS after wave 1. The resulting sample of parents consists of 4,711 mothers and 3,546 fathers.

Information about the focal child is collected during the primary caregiver's interview. Accordingly, the sample of children is limited to parents which satisfy the aforementioned criteria. Because only one parent, the primary caregiver, is interviewed in wave 6 and 93% of the primary caregivers are mothers, the sample of children is restricted to children whose mother is the primary caregiver. Lastly, the sample is limited to children which completed the survey in wave 6. Thus the sample analysis of children consists of 3,122 children.

[9]Each city is categorized as either a "large sample" city or "small sample" city. A "large sample" city is defined as a city for which a sample of approximately 325 families are surveyed; while a "small sample" city is one in which approximately 100 families are surveyed. "Large sample" cities are Detroit, Milwaukee, San Jose, Oakland, New York, Newark, Baltimore, Richmond, and Austin. "Small sample" cities are Boston, Toledo, Pittsburgh, Norfolk, Philadelphia, Jacksonville, Chicago, Indianapolis, Nashville, San Antonio, and Corpus Christi.

[10]Nonresident fathers are defined as fathers not living in the same residence as the focal child.

Table 1.1 provides descriptive statistics by parental gender. The racial composition of parents are 48% Black, 27% Hispanic, and 21% White with a mean age of 30 for mothers and 32 for fathers.[11] The highest education level of approximately 33% of parents is 'Some College', only 13% of mothers and 15% of fathers have college degrees.

1.2.3 Assigning Exposure to School Shootings

I assign exposure to school shootings using information on the city and exact date of the shooting relative to the month in which a family was interviewed. Given that for every survey wave, families in the same city are interviewed in different months throughout the year, this means that there is variation in shooting exposure within each city by wave. For example, consider a shooting that took place in Chicago in February of 2000, which is during survey wave 2. Family A in Chicago was interviewed one month prior to the shooting, while family B in Chicago was interviewed the month after the shooting, then family B would be considered exposed to the shooting in wave 2, while family A would be considered unexposed. In Table 1.2, I show the percentage of parental shooting exposure by gender and wave. Columns 2 and 4 identify the number of mothers and fathers interviewed at each wave, respectively; while columns 3 and 5 display the percentage of parental shooting exposure.[12] Wave 2 reflects the lowest percentage of parental exposure for both mothers and fathers, 14%, wave 5 accounts for the largest percentage of interviewed parents that are exposed to school shootings, 54% of mothers and 49% of fathers. The city for each parent is identified only in the baseline, but the states in which they reside are disclosed for all interviews. Thus, there is some measurement error in assignment of exposure due to the fact that families could move away from the cities in which they resided at the baseline. However, my results are similar if I limit the analysis to families who are always residing in the same state as they were at baseline.[13]

[11] The mean baseline age for mothers is 25 and 28 for fathers.

[12] For wave 6, only the primary caregiver is interviewed.

[13] Eighty-six percent of mothers remained in the state at wave two. At wave 6, the percentage of mothers residing in baseline state decreases to 56% in wave 6. At waves 3, 4, and 5 the percentage of mothers living within the baseline state are 81%, 77% and 65%, respectively.

Lastly, the restricted-use version of the FFCWS data contains a linkage to data from the Uniform Crime Reports, which provides county-level data on crime rates in the parent's county of residence. I focus on the violent crime rate in my analysis and use it to account for the overall level of crime to which a family is exposed in some regression specifications. The mean violent crime rate across waves is 0.78 for parents.[14]

FFCWS Mental Health and Educational Expectation Outcomes

As outcomes, I study several measures of parental mental health and their children's expectations regarding education. Parental mental health outcomes, which consists of (1) indicators for level of life satisfaction: "very satisfied", "somewhat satisfied", "somewhat dissatisfied", and "very dissatisfied"; and a (2) binary variable equal to 1 if the parent is likely to have experienced a major depressive episode, zero otherwise.[15] [16] Also, I analyze the mental health of the children. To do this, I construct a binary variable equal to 1 if the child receives treatment for depression, zero otherwise.[17]

In wave 6, the focal children and their primary caregiver answered questions that assess the educational outlook for the child. The questions are: (Question 1-Respondent: child) "How likely are you to graduate from college?", (Question 2-Respondent: mother) "How likely is your child to graduate college?", (Question 3-Respondent: child) "How important to you that you graduate college?", and (Question 4-Respondent: child) "How important [is it] to the primary caregiver that you graduate college?" Accordingly, I create binary indicators for each answer choice as educational expectation outcomes: (Questions 1 and 2)

[14] Violent crime consists of murder, rape, robbery, and aggravated assault.

[15] Parental depression is measured in waves 2-6 and parental rating of overall satisfaction is reported in waves 3-6.

[16] The depressive episode variable is a FFCWS constructed variable. The variable was constructed by asking parents seven questions to assess whether the parent has likely experienced a major depressive episode. The questions include: lost interest, feeling tired, weight gain of at least 10 pounds, sleeping difficulty, trouble concentrating, feeling sad, and thoughts of death (for Research on Child Wellbeing, 2018; Walters *et al.*, 2002). The questions are scored by summing the number of symptoms experienced by the parent. If the parent scores three or more, they are identified to have likely experienced a major depressive episode.

[17] Child's mental health is measured in waves 5 and 6.

"very likely," "somewhat likely," "somewhat unlikely," and "very unlikely"; (Questions 3 and 4) "very important," "somewhat important", and "not very important."

In addition to studying the outcomes described above, I construct aggregate indices to reduce concerns about multiple hypothesis testing and improve the statistical power of the analysis (Kling *et al.,* 2007). To construct the indices, I first orient the outcome variables such that favorable responses represent a higher value. For example, for the variable capturing whether a parent experiences depression, I orient it such that a 1 represents "not depressed" and a 0 represents "depressed". Then, for each outcome, I calculate the z-score by subtracting the control group mean and dividing by the control group standard deviation, where the control group refers to the set of observations for whom there is no shooting exposure. The index is then an unweighted average of the z-scores. The mental health index includes the following variables: indicator equal to 1 if the parent has symptoms of major depressive episodes, zero otherwise, and categorical variable of the self-reported life satisfaction ratings of parents. Parents rate life satisfaction as either very satisfied, somewhat satisfied, somewhat dissatisfied, or very dissatisfied. The educational expectations index is composed of the following four categorical variables: the child's assessment of his or her own likelihood of graduating college (possible responses are very likely, somewhat likely, somewhat unlikely, very unlikely), primary caregiver's assessment of the child's likelihood of graduating college (possible responses are very likely, somewhat likely, somewhat unlikely, very unlikely), child's valuation of the importance of graduating college (responses include very important, somewhat important, not very important), and the child's perception of the level of importance their mother places on graduating college (responses include very important, somewhat important, not very important).

1.3 EMPIRICAL DESIGN

My goal is to estimate the causal impact of exposure to school shootings on parental mental health and wellbeing, as well as the educational expectations of their children. To do so, I use a type of different-in-difference design by exploiting the exogenous variation in the relative timing of shootings and interview dates among parents and children living in the same city. Specifically, I estimate the following model for each individual i, living in baseline city c, at wave w:

$$Y_{icw} = \beta_0 + \beta_1 NumberofSchoolShootings_{icw} + \beta_2 X_{icw} + \gamma_{cw} + u_{icw} \tag{1.1}$$

Y_{icw} is an outcome of interest, such as an indicator for parental likelihood of experiencing a major depressive episode. $NumberofSchoolShootings$ is the key explanatory variable, which is the number school shootings in the individual's city in that wave that occur by the interview date of the following wave. X_{icw} is a vector of parental and child characteristics that contains indicators for parental marital status (equal to 1 if single, and 0 otherwise), parental race/ethnicity (Black, Hispanic, White, other), parental education (less than high school, high school diploma, some college, bachelor's degree or higher), parental age (15-25, 26-35, 36-45, 46-55, and 55+) and child's age (0-5, 6-10, 11-15, and 15+). γ_{cw} captures city-by-wave fixed effects (i.e., an indicator for each of the 120 city-by-wave cells), accounting for all time-invariant and time-varying differences across cities and city-specific shocks that may take place in any given wave. The key coefficient of interest β_1, which measures the average effect of being exposed to an additional school shooting on the outcome of interest. The city-by-wave fixed effects causes β_1 to solely depend on the randomly generated variation in the relative timing of family interviews and school shootings within a given city and within a particular survey wave. Therefore, the method only considers analysis sample families living within cities which experience variation in school shooting exposure within a given survey

wave (Sharkey, 2010). Standard errors are clustered at the level of variation, city by wave (note, there are 120 clusters in my analysis).

I estimate equation (1), both for the overall sample and for the sample split by marital status. Prior research suggests that the pathways through which school shootings may affect parents manifest differently by parental gender and marital status. Single parents face the same stressors as married parents, but they typically experience additional stressors such as low social support, financial hardship, less time spent with children, and childcare issues (Cairney, Thorpe, *et al.,* 1999; Cairney, Boyle, *et al.,* 2003; Wade *et al.,* 2011). However, specifically for mothers, negative life events have a greater positive correlation with depression among married mothers than among single mothers (Cairney, Boyle, *et al.,* 2003). I am interested in examining whether school shooting exposure affects marital types differently. To do this, I combine unmarried parents by gender to form single/cohabiting groups, which constitute 75% of the overall sample due to the FFCWS oversampling of unmarried parents. The remaining parents, separated by gender, comprise the married groups.

To interpret the main treatment coefficient, β_1, as causal, I rely on a standard difference-in-differences assumption of parallel trends. Specifically, it must be that the timing of school shootings across cities is not correlated with other time-varying differences between cites that also affect my outcomes of interest. As one check of this assumption, I estimate a regression in which I collapse the data to the city-by-wave level and study the correlation between the timing of school shootings and other local city characteristics, including the unemployment rate, annual consumer sentiment index, and average annual personal income, with city and wave fixed effects. Results are reported in Table 1.7.

1.4 RESULTS

Table 1.3 presents my main results on the effects of exposure to school shootings on maternal mental health and wellbeing. Panel A shows results for my whole sample, while Panels B and C split the sample by maternal marital status (married versus single/cohabiting). As outcomes, I use both the aggregate mental health well-being index and the individual components of the index, which is a binary indicator for having a depressive episode and a categorical variable for the question regarding life satisfaction (very satisfied, somewhat satisfied, somewhat dissatisfied, and very dissatisfied). For the overall sample, the coefficient of the index outcome is negative, but not statistically significant at conventional levels. However, when I split the sample by maternal marital status in Panels B and C, I uncover important effect heterogeneity. Specifically, I find that the overall mental health index is 0.100 standard deviations lower following exposure to a school shooting among married mothers. By contrast, the coefficient for single/cohabiting mothers is very small in magnitude and not statistically significant. For the individual outcome components of the index, I find that the decline in overall mental wellbeing among married mothers is driven by a reduction in the likelihood that they report being very satisfied with their life, and an accompanying increase in the likelihood of reporting being somewhat satisfied. Additionally, my results show that married mothers are 2.4 percentage points more likely to experience a depressive episode when exposed to a school shooting. For single/cohabiting mothers, I find there to be a decreased likelihood that they report being somewhat satisfied with their life (and an accompanying increase in the likelihood of reporting being disatisfied).

Table 1.4 presents the results for fathers in my sample. Similar to the mothers, I do not find a statistically significant effect on the fathers' aggregate wellbeing index. Unlike mothers, differences in martial status do not reveal statistically significant effects of school shooting exposure on fathers.

Table 1.5 presents results on children's educational expectations. In the overall sample, I find that children have a 0.093 standard deviation lower educational expectation index following exposure to a shooting. As with the results on maternal mental health, the effect is larger in magnitude among families with married parents. Individual outcome analyses indicate that the overall effect is operating on several margins: children are less likely to state that they are "very likely" to graduate college, and more likely to report that they are "somewhat likely" to do so. Shooting-exposed children are less likely to state that graduating from college is "very important," with a corresponding increase in reporting "somewhat important." Though greater in magnitude, a similar pattern is found with children of married parents. Lastly, shooting-exposed children with married parents are less likely to perceive that their mother values the child graduating from college as "very important" and are more likely to perceive that their mother values the child graduating college as "somewhat important."

Since children's own mental health in the aftermath of a school shooting is a central mechanism by which parental wellbeing and parents' and children's expectations regarding children's educational attainment could be influenced, I also analyze as an outcome an indicator for the mother reporting that their child has received treatment for depression. Table 1.6 presents the coefficients of the main treatment variable (exposure to a school shooting) for the overall sample and for the sample split by parental marital status. I find that shooting-exposed children are 0.5 percentage points more likely to be treated with an anti-depressant medication (an 25% effect relative to the sample mean). As with my other findings, the effect is stronger among children with married parents.

1.4.1 Sensitivity Analysis

Residential Location

Since I assign exposure to shootings using information on parents' baseline city of residence, a key assumption for my analysis is that families continue to reside within the baseline city in

each wave. To gauge the role of measurement error due to migration out of the baseline city in affecting my results, I replicate the main regression model using sub-samples limited to mothers and fathers who report still living in the same state as at baseline in each wave (there is unfortunately no information on whether they are still in the same city). In addition, I check whether mobility out of state is affected by shooting exposure by estimating equation (1) using as an outcome an indicator for the parent leaving the state.

Tables 1.8-1.11 present the results. I find that exposure to a school shooting does not significantly alter the likelihood that either parent leaves the state, and the results for the sub-sample of parents who do not leave the state are similar to those for the overall sample.

Controlling for the Local Violent Crime Rate

One concern with interpreting my estimates is that the effect of exposure to a school shooting in a given city captures a broader effect of violence in the local community (Christens & Speer, 2005). Put differently, given that school shootings are more likely to occur in urban communities with violence in other settings, my treatment coefficient may be capturing the impacts of broader violence exposure rather than the distinct impact of a school shooting. Tables 1.12-1.15 present results in which I include a control for the violent crime rate in the county of residence of each mother and father in each wave.[18] Notably, the inclusion of this control variable does not meaningfully alter the main treatment coefficient for mothers. There are some small changes in the significance of the estimates for fathers, but the broad pattern remains the same. Thus, it appears that my main estimates are indeed capturing the unique impacts of exposure to school shootings rather than general crime in the local area.

[18]The violent crime rate is reported by the National Archive of Criminal Justice Data (NACJD). For each wave the crime rates (per 100,000 people) are reported for the residence of both the biological mother and father of focal child. In wave 6, the rates are provided for the residence of the primary caregiver of child. The violent crime rate is divided by 1000 to adjust unit measure.

1.4.2 Discussion

In recent decades, it has become necessary for communities in the United States to develop support channels for those exposed to school shootings. Understanding the problems left by school shooting exposure on survivors will help to effectively identify and allocate needed resources to affected communities. Through the use of unique data, my research finds that school shooting exposure affects single/cohabiting and married family composition differently. I provide evidence that shooting exposure leads to decreases in the mental health of married mothers and fathers, and the mental health and educational expectations of children. This result supports literature which finds that negative life events have greater negative correlation to the mental health in married mothers than unmarried mothers (Cairney, Boyle, *et al.*, 2003).[19] An additional consideration is that unobserved daily stress and challenges borne by single-parent mothers are more acute than infrequently occurring school shootings.

Current school shooting literature only investigates causal effects of shooting exposure on children. Though children are directly exposed, parents and those in the community are indirectly impacted by this type of violence because it brings to light the vulnerability of children and adults alike, to those who seek to do harm. For married mothers, school shooting exposure leads to a decreased satisfaction with life. I identify that marginal increases in exposure cause increased likelihood of depressive episodes to wedded fathers. These findings contrast with those of Bharadwaj *et al.* (2021). In their research they estimate causal effects of a summer camp mass shooting on parents but find no significant causal effects by marital status. Nonetheless, after performing two robustness checks, the main results of this analysis are notably persistent.

Previous work by Rossin-Slater *et al.*(2020) found increased antidepressant usage in areas where fatal school shootings occurred. Though the school shootings used in this analysis are

[19]Negative life events refer to non-reoccurring experiences such as physical assault, financial crisis, and miscarriage.

largely nonfatal, I document a similar finding that children of exposed families have an increased likelihood of receiving treatment for depression. The effect is largely observed for children of traditional homes. Obtaining medical help to address a child's mental health can require time off from work to attend doctor appointments and may require monetary expenses, both of which contribute to the hardships of single/cohabiting families (Folk, 1996; McLanahan & Carlson, 2002). For this reason, single/cohabiting families may be less likely to seek medical assistance for the child's mental health.

Lastly, I find that children in families exposed to school shootings are less likely to have high educational aspirations. This result corroborates research by Cabral *et al.*(2020) and Deb and Gangaram (2021). Both studies identify declines in educational attainment for exposed children. These results also support the conclusion of other research which document a negative relationship between violence and educational aspiration and attainment of children (Duque, 2019; Barrera Osorio & Ibáñez Londoño, 2004).

As previously mentioned, the inability to locate parents at the city level in follow-up waves is a limitation of this study. An additional limitation is the small sample of fathers surveyed at wave 6. Nonetheless, the estimation results remain robust to the empirical specifications used in the study. For that reason, it is likely that the coefficient estimates for fathers are below the true effect.

1.5 CONCLUSION

After shootings in schools such as the Uvalde, TX Elementary School, which to date, claimed the most lives of all school shooting incidents and captured the attention of the United States and world, there are calls for policy changes and greater protection for schools (Mangan, 2022; BBC, 2022). However most school shooting occurrences, such as those in my study, do not receive mass media coverage. Consequently, the same calls to action are not as loud for these school shooting incidents but families within these communities are no less

impacted. Recognizing school shooting effects on families can guide policy initiatives in providing effective support.

My research shows that school shooting exposure causes negative effects on the mental health of parents and children. Specifically, I find a decline in the overall mental wellbeing among married mothers and increased likelihood of married fathers experiencing depression due to school shooting exposure. Additionally, children exposed to school shootings have poorer educational expectations than unexposed children. From these results, it is rational to conclude that mental health services are needed in communities which experience school shootings and should be provided to families both directly and indirectly exposed within the community, despite the severity of the incident. Future research is needed to understand whether parents exhibit long-run effects and whether the availability of mental health services diminishes exposure effects in the long-run.

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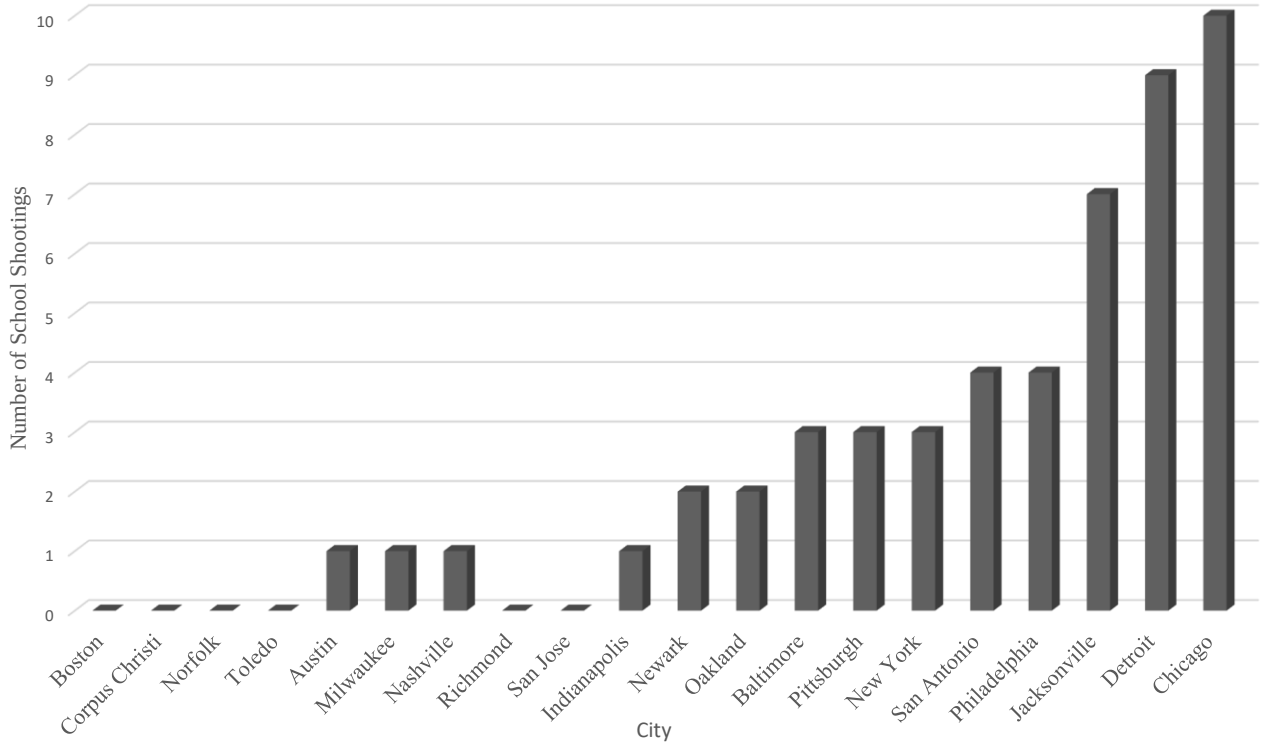
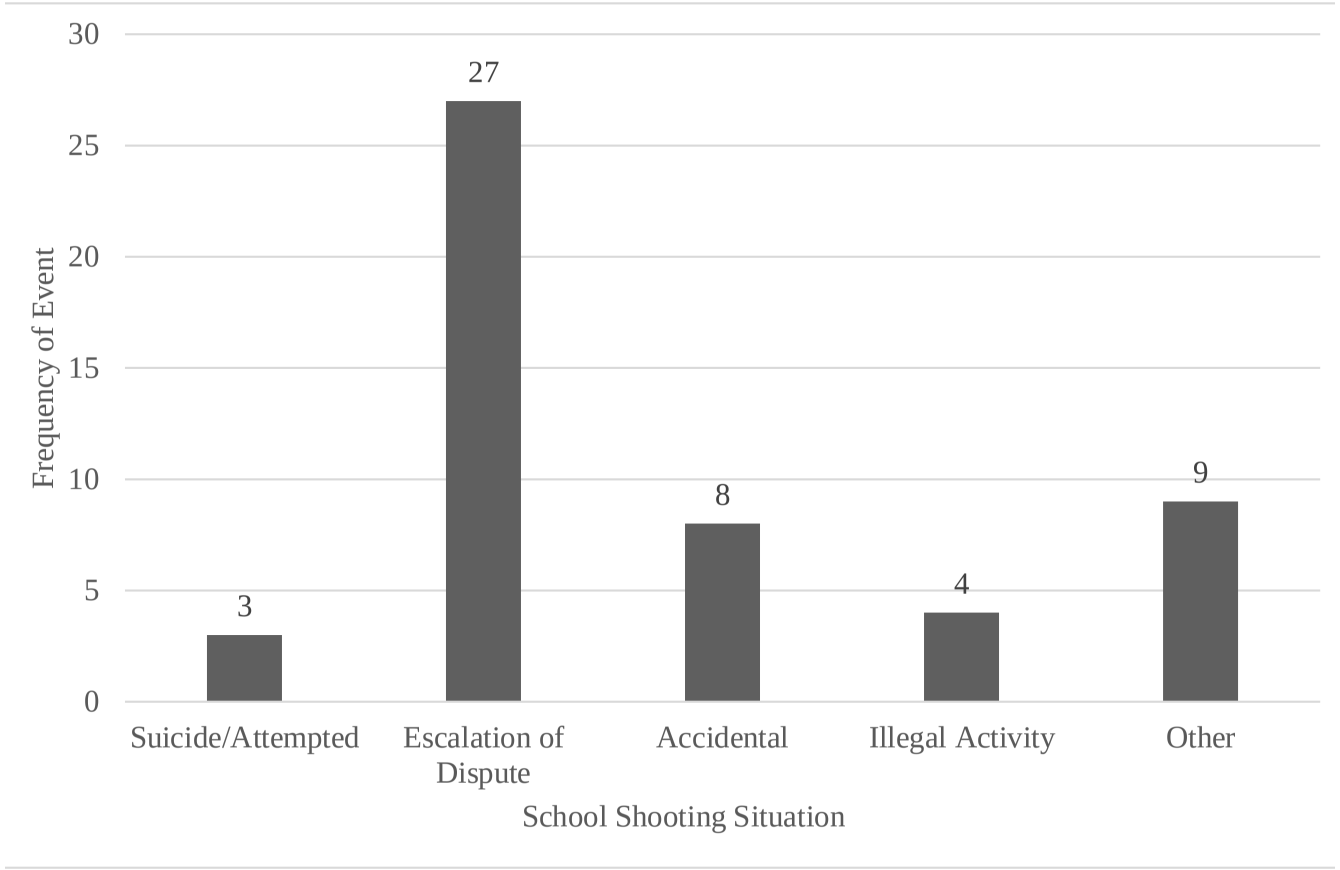
1.6 TABLES AND FIGURES

Figure 1.1: Total Number of School Shootings by City During Waves 2-6



Notes : School shooting exposures by city between February 1998 – March 2017 to parents of the Fragile Families Child Wellbeing Study. School shootings are defined as an event in which "a gun is brandished, is fired, or a bullet hits school property for any reason, regardless of the number of victims, time, day of the week, or reason" (Riedman & O'Neill, n.d.). School shooting data is compiled by the Center for Homeland Defense and Security's K-12 School Shooting Database. In this analysis, only school shootings that occur during school hours on school property are considered for a total of 51 shootings.

Figure 1.2: Types of School Shooting Events



Notes : Frequency of school shooting events by type of situation in cities of the Fragile Families Child Wellbeing Study. The situation descriptions are suicide/attempted, escalation of dispute, accidental, illegal activity, and other. Shootings are classified based upon the narrative gathered by news articles, websites, newspapers, blogs, government reports, the Department of Education, and mainstream media. School shooting records are sourced from the Center for Homeland Defense and Security's K-12 School Shooting Database. These 51 shootings occurred between February 1998 – March 2017.

Table 1.1: Summary Statistics by Parental Gender

	Mothers	Fathers
Average number of school shooting exposure over waves 2-6	0.303	0.257
	(0.677)	(0.641)
Black	0.476	0.471
	(0.499)	(0.499)
Hispanic	0.273	0.276
	(0.445)	(0.447)
White	0.211	0.210
	(0.408)	(0.407)
Other ethnicity	0.0410	0.0434
	(0.198)	(0.204)
Age	30.22	31.51
	(7.863)	(8.020)
Less than high school	0.278	0.262
	(0.448)	(0.440)
High school diploma	0.264	0.260
	(0.441)	(0.439)
Some college	0.326	0.327
	(0.469)	(0.469)
BA or higher	0.132	0.151
	(0.339)	(0.358)
Violent crime rate (per 100 persons)	0.777	0.779
	(0.437)	(0.438)
Left baseline residential state	0.149	0.124
	(0.356)	(0.329)
Child's age	6.473	
	(5.079)	
Child is a boy	0.522	
	(0.500)	
Observations	28266	21276

Table 1.2: Percentage of Parental School Shooting Exposure by Wave

Wave	Number of Mothers Interviewed	Percentage of Mothers Exposed to School Shooting	Number of Fathers Interviewed	Percentage of Fathers Exposed to School Shooting
1	4,711	–	3,546	–
2	4,364	14%	3,135	14%
3	4,231	23%	2,966	21%
4	4,139	23%	2,792	22%
5	3,515	54%	2,348	49%
6	3,146	34%	227	24%

Notes : Percentage of shooting exposed parents by gender and wave. Fragile Families Child Wellbeing Study interviewed both parents at waves 1-5. For wave 6, only the primary caregiver is interviewed; 93% of the primary caregivers are mothers. Each wave interviewed parents are assumed to live in the same city that is identified in wave 1. Columns 2 and 4 identify the number of mothers and fathers interviewed at each wave, respectively. Figures in cols. 3 and 5 are the percentage of interviewed mothers and fathers that are exposed to school shooting events in each wave. The percentages in col. 3 are calculated at each wave by dividing the number of shooting exposed mothers by the number of interviewed mothers. The same calculation is used to determine the percentage of shooting exposed fathers. I determine shooting exposure by taking the sum of school shooting events that occur between the parent's interview date at each wave in their city of residence.

Table 1.3: Effects of Exposure to School Shootings on Mothers' Mental Health and Life Satisfaction

	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatis-fied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Mothers						
# of School Shootings	−0.034	0.012	−0.019*	0.025***	−0.015	0.009**
	(0.021)	(0.008)	(0.011)	(0.008)	(0.009)	(0.004)
Mean of Dep. Var.	0.00241	0.111	0.442	0.447	0.0895	0.0215
Parent-wave observations	19336	19287	14966	14966	14966	14966
B. Married Mothers						
# of School Shootings	−0.100***	0.024*	−0.067***	0.061***	0.003	0.002
	(0.033)	(0.014)	(0.019)	(0.022)	(0.013)	(0.006)
Mean of Dep. Var.	0.137	0.0896	0.586	0.357	0.0447	0.0119
Parent-wave observations	6772	6760	5430	5430	5430	5430
C. Single and Cohabiting Mothers						
# of School Shootings	−0.000	0.006	0.003	0.012	−0.027***	0.012***
	(0.026)	(0.010)	(0.014)	(0.011)	(0.010)	(0.005)
Mean of Dep. Var.	−0.0638	0.121	0.360	0.498	0.115	0.0270
Parent-wave observations	12564	12527	9536	9536	9536	9536

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 6 separate regressions. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is the key explanatory variable, which is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for mothers of all family compositions: married, single, and cohabiting. Panel B shows results for married mothers and Panel C considers single and cohabiting mothers. For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.4: Effects of Exposure to School Shootings on Fathers' Mental Health and Life Satisfaction

	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatisfied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Fathers						
# of School Shootings	0.011	0.004	0.004	0.011	−0.011	−0.004
	(0.025)	(0.012)	(0.010)	(0.013)	(0.009)	(0.004)
Mean of Dep. Var.	0.0105	0.0656	0.433	0.446	0.0947	0.0265
Parent-wave observations	10921	10919	7862	7862	7862	7862
B. Married Fathers						
# of School Shootings	−0.024	0.013	−0.014	0.013	0.002	−0.000
	(0.036)	(0.010)	(0.029)	(0.024)	(0.008)	(0.004)
Mean of Dep. Var.	0.152	0.0434	0.559	0.392	0.0420	0.00764
Parent-wave observations	4512	4512	3374	3374	3374	3374
C. Single and Cohabiting Fathers						
# of School Shootings	0.034	−0.004	0.017	0.001	−0.014	−0.005
	(0.045)	(0.020)	(0.016)	(0.018)	(0.010)	(0.007)
Mean of Dep. Var.	−0.0728	0.0787	0.345	0.484	0.131	0.0396
Parent-wave observations	6409	6407	4488	4488	4488	4488

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 6 separate regressions. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the father's baseline city of residence, where $\#ofSchoolShootings$ is the key explanatory variable, which is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for fathers of all family compositions: married, single, and cohabiting. Panel B shows results for married fathers and Panel C considers single and cohabiting fathers. For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.5: Effects of Exposure to School Shootings on Children's Educational Expectations

	Educational Expectation Index	Mother's Assessment of the Child's Llikelihood of Graduating College				Child's Assessment of the Llikelihood of Graduating College			
	Educational Expectation	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Children of all Family Compositions									
# of School Shootings	−0.093*	−0.016	0.011	0.004	0.001	−0.071	0.068	0.007	−0.005
	(0.044)	(0.023)	(0.021)	(0.011)	(0.015)	(0.045)	(0.046)	(0.004)	(0.009)
Mean of Dep. Var.	−0.00666	0.719	0.228	0.0313	0.0217	0.652	0.321	0.0196	0.00788
Parent-wave observations	3122	3109	3109	3109	3109	2993	2993	2993	2993
B. Children Whose Mother is Married									
# of School Shootings	−0.178*	−0.031	0.012	0.004	0.015	−0.105**	0.122**	0.005	−0.022
	(0.085)	(0.033)	(0.034)	(0.012)	(0.025)	(0.045)	(0.045)	(0.004)	(0.018)
Mean of Dep. Var.	0.0640	0.773	0.186	0.0261	0.0147	0.703	0.278	0.0152	0.00422
Parent-wave observations	1221	1216	1216	1216	1216	1178	1178	1178	1178
C. Children Whose Mother is Single or Cohabiting									
# of School Shootings	−0.031	−0.009	0.014	0.004	−0.009	−0.042	0.025	0.009	0.008
	(0.072)	(0.038)	(0.029)	(0.016)	(0.017)	(0.051)	(0.051)	(0.007)	(0.005)
Mean of Dep. Var.	−0.0439	0.684	0.255	0.0346	0.0262	0.625	0.344	0.0218	0.00981
Parent-wave observations	1901	1893	1893	1893	1893	1815	1815	1815	1815

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: *(continued)* Effects of Exposure to School Shootings on Children's Educational Expectations

	Child's Valuation of the Importance of Graduating College			Child's Perception of the Mother's Valuation of Graduating College		
	Very Important	Somewhat Important	Not Very Important	Very Important	Somewhat Important	Not Very Important
	(10)	(11)	(12)	(13)	(14)	(15)
A. Children of all Family Compositions						
# of School Shootings	−0.030*	0.031*	−0.000	−0.016	0.006	0.010*
	(0.017)	(0.016)	(0.007)	(0.021)	(0.018)	(0.005)
Mean of Dep. Var.	0.852	0.131	0.0166	0.923	0.0706	0.00633
Parent-wave observations	2997	2997	2997	2983	2983	2983
B. Children Whose Mother is Married						
# of School Shootings	−0.079**	0.073*	0.006	−0.066***	0.062***	0.004
	(0.035)	(0.039)	(0.018)	(0.021)	(0.021)	(0.002)
Mean of Dep. Var.	0.865	0.124	0.0110	0.924	0.0712	0.00508
Parent-wave observations	1179	1179	1179	1174	1174	1174
C. Children Whose Mother is Single or Cohabiting						
# of School Shootings	0.007	−0.002	−0.005	0.020	−0.034	0.014
	(0.037)	(0.036)	(0.007)	(0.032)	(0.030)	(0.009)
Mean of Dep. Var.	0.846	0.135	0.0196	0.923	0.0703	0.00714
Parent-wave observations	1818	1818	1818	1809	1809	1809

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 15 separate regressions. Units of observation are person by wave. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is the key explanatory variable, which is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.6: Effects of Exposure to School Shootings on Children's Mental Health

	Child Receives Treatment for Depression
A. Children of all Family Compositions	
# of School Shootings	0.005*
	(0.003)
Mean of Dep. Var.	0.0204
Parent-wave observations	6587
B. Children Whose Mother is Married	
# of School Shootings	0.005*
	(0.003)
Mean of Dep. Var.	0.0192
Parent-wave observations	2542
C. Children Whose Mother is Single or Cohabiting	
# of School Shootings	0.004
	(0.003)
Mean of Dep. Var.	0.0211
Parent-wave observations	4045

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : Units of observation are person by wave. The outcome is shown in the column heading. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is the key explanatory variable, which is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. *Child Receives Treatment for Depression* is an indicator variable that equals 1 if the child takes medication for depression, zero otherwise. For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.7: Effects of Exposure to School Shootings on Cities-Parallel Trend Regressions

	Unemployment Rate	Consumer Sentiment Index	Personal Income
	(1)	(2)	(3)
# of School Shootings	0.216	−0.150	−642.100
	(0.229)	(0.930)	(393.199)
Mean of Dep. Var.	6.594%	89.91	40,518.54
City-wave observations	120	120	120

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from three separate regressions. The table reports results from estimating the effects of school shooting exposure in each baseline city of FFCWS, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in each city and wave that occur by the city's interview date of the following wave. The dependent variables in cols. 1-3 are city-level annual average characteristics for each city's wave-year. Consumer sentiment index measures the optimism consumers feel about their personal finances and the overall economy. The index base period is 1966. Index values greater than 100 infer that consumers are more confident in the economy than they were in 1966. Personal income is reported in nominal dollars corresponding to the year in which interviews began in each city at each wave. All regressions control for city fixed effects and wave fixed effects. Standard errors are robust.

Table 1.8: Effects of Exposure to School Shootings on the Mental Health and Life Satisfaction of Mothers that Live in the Baseline State for All Waves

	Left State	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatis-fied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. All Mothers							
# of School Shootings	0.003	−0.027	0.011	−0.020*	0.034***	−0.023***	0.009**
	(0.010)	(0.017)	(0.009)	(0.011)	(0.009)	(0.008)	(0.004)
Mean of Dep. Var.	–	0.0135	0.107	0.449	0.443	0.0873	0.0215
Parent-wave observations	19244	16448	16410	12700	12700	12700	12700
B. Married Mothers							
# of School Shootings	−0.010	−0.082**	0.015	−0.064**	0.064**	−0.008	0.007**
	(0.018)	(0.037)	(0.017)	(0.025)	(0.029)	(0.016)	(0.004)
Mean of Dep. Var.	–	0.149	0.0859	0.591	0.354	0.0430	0.0119
Parent-wave observations	6728	5566	5554	4454	4454	4454	4454
C. Single and Cohabiting Mothers							
# of School Shootings	0.007	−0.002	0.009	−0.002	0.026*	−0.033***	0.009*
	(0.012)	(0.025)	(0.011)	(0.014)	(0.013)	(0.010)	(0.005)
Mean of Dep. Var.	–	−0.0498	0.117	0.372	0.490	0.111	0.0267
Parent-wave observations	12516	10882	10856	8246	8246	8246	8246

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Column 1 presents the results for $Leftstate$, an indicator variable equal to 1 if the mother moved out of state, zero otherwise. For regressions 2-7, the sample is restricted to parents which never leave their baseline state. Panel A presents results for mothers of all family compositions: married, single, and cohabiting. Panel B shows results for married mothers and Panel C considers single and cohabiting mothers. For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.9: Effects of Exposure to School Shootings on the Mental Health and Life Satisfaction of Fathers that Live in the Baseline State for All Waves

	Left State	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatisfied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. All Fathers							
# of School Shootings	−0.000	0.015	0.004	0.005	0.014	−0.016*	−0.002
	(0.011)	(0.031)	(0.014)	(0.011)	(0.015)	(0.010)	(0.004)
Mean of Dep. Var.	–	0.0138	0.0646	0.435	0.442	0.0947	0.0274
Parent-wave observations	10815	9556	9554	6864	6864	6864	6864
B. Married Fathers							
# of School Shootings	−0.014	−0.024	0.016	−0.013	0.017	−0.002	−0.002
	(0.020)	(0.044)	(0.012)	(0.034)	(0.029)	(0.010)	(0.004)
Mean of Dep. Var.	–	0.159	0.0419	0.565	0.387	0.0410	0.00660
Parent-wave observations	4485	3823	3823	2853	2853	2853	2853
C. Single and Cohabiting Fathers							
# of School Shootings	0.005	0.036	−0.004	0.017	0.002	−0.019	−0.002
	(0.012)	(0.049)	(0.023)	(0.017)	(0.021)	(0.012)	(0.006)
Mean of Dep. Var.	–	−0.0671	0.0773	0.350	0.479	0.130	0.0411
Parent-wave observations	6330	5733	5731	4011	4011	4011	4011

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the father's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Column 1 presents the results for $Leftstate$, an indicator variable equal to 1 if the father moved out of state, zero otherwise. For regressions 2-7, the sample is restricted to fathers which never leave their baseline state. Panel A presents results for fathers of all family compositions: married, single, and cohabiting. Panel B shows results for married fathers and Panel C considers single and cohabiting fathers. For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.10: Effects of Exposure to School Shootings on the Educational Expectations of Children Whose Mother Lives in the Baseline State for All Waves

	Likelihood of Leaving State	Educational Expectation Index
	Left State	Educational Expectation
	(1)	(2)
A. Children of all Family Compositions		
# of School Shootings	0.003	−0.100*
	(0.010)	(0.051)
Mean of Dep. Var.	–	−0.0168
Parent-wave observations	19244	2632
B. Children Whose Mother is Married		
# of School Shootings	−0.010	−0.184*
	(0.018)	(0.096)
Mean of Dep. Var.	–	0.0488
Parent-wave observations	6728	997
C. Children Whose Mother is Single or Cohabiting		
# of School Shootings	0.007	−0.039
	(0.012)	(0.092)
Mean of Dep. Var.	–	−0.0486
Parent-wave observations	12516	1635

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 16 separate regressions. Units of observation are person by wave. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Column 1 presents the results for $Leftstate$, an indicator variable equal to 1 if the mother moved out of state, zero otherwise. For regressions 2-16, the sample is restricted to mothers which never leave their baseline state. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses. See text for details.

Table 1.10: *(continued)* Effects of Exposure to School Shootings on the Educational Expectations of Children Whose Mother Lives in the Baseline State for All Waves

	Mother's Assessment of the Child's Llikelihood of Graduating College				Child's Assessment of the Llikelihood of Graduating College			
	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely
	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Children of all Family Compositions								
# of School Shootings	−0.009	0.013	0.001	−0.006	−0.094	0.089	0.005	−0.000
	(0.025)	(0.023)	(0.013)	(0.015)	(0.059)	(0.058)	(0.005)	(0.007)
Mean of Dep. Var.	0.713	0.230	0.0337	0.0227	0.649	0.323	0.0204	0.00781
Parent-wave observations	2621	2621	2621	2621	2516	2516	2516	2516
B. Children Whose Mother is Married								
# of School Shootings	−0.028	0.019	0.004	0.005	−0.132**	0.140**	0.003	−0.012
	(0.049)	(0.047)	(0.014)	(0.018)	(0.062)	(0.055)	(0.005)	(0.014)
Mean of Dep. Var.	0.765	0.192	0.0301	0.0130	0.692	0.288	0.0156	0.00416
Parent-wave observations	993	993	993	993	959	959	959	959
C. Children Whose Mother is Single or Cohabiting								
# of School Shootings	0.003	0.011	0.000	−0.014	−0.063	0.047	0.007	0.009
	(0.046)	(0.035)	(0.019)	(0.021)	(0.073)	(0.074)	(0.007)	(0.005)
Mean of Dep. Var.	0.682	0.253	0.0360	0.0287	0.628	0.339	0.0227	0.00958
Parent-wave observations	1628	1628	1628	1628	1557	1557	1557	1557

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: *(continued)* Effects of Exposure to School Shootings on the Educational Expectations of Children Whose Mother Lives in the Baseline State for All Waves

	Children's Valuation of the Importance of Graduating College			Child's Perception of the Mother's Valuation of Graduating College		
	Very Important	Somewhat Important	Not Very Important	Very Important	Somewhat Important	Not Very Important
	(11)	(12)	(13)	(14)	(15)	(16)
A. Children of all Family Compositions						
# of School Shootings	−0.028	0.036	−0.009	−0.024	0.012	0.012*
	(0.022)	(0.023)	(0.006)	(0.027)	(0.022)	(0.007)
Mean of Dep. Var.	0.848	0.134	0.0180	0.925	0.0683	0.00675
Parent-wave observations	2519	2519	2519	2508	2508	2508
B. Children Whose Mother is Married						
# of School Shootings	−0.078	0.088*	−0.009	−0.071**	0.068**	0.003
	(0.047)	(0.047)	(0.014)	(0.026)	(0.026)	(0.002)
Mean of Dep. Var.	0.861	0.127	0.0125	0.927	0.0668	0.00626
Parent-wave observations	960	960	960	956	956	956
C. Children Whose Mother is Single or Cohabiting						
# of School Shootings	0.012	−0.003	−0.009	0.011	−0.028	0.017
	(0.044)	(0.044)	(0.007)	(0.040)	(0.037)	(0.012)
Mean of Dep. Var.	0.842	0.137	0.0206	0.924	0.0691	0.00704
Parent-wave observations	1559	1559	1559	1552	1552	1552

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Effects of Exposure to School Shootings on Mental Health of Children Whose Mother Lives in the Baseline State for All Waves

	Child Receives Treatment for Depression
A. Children of all Family Compositions	
# of School Shootings	0.005
	(0.003)
Mean of Dep. Var.	0.0217
Parent-wave observations	5558
B. Married Mothers	
# of School Shootings	0.004
	(0.003)
Mean of Dep. Var.	0.0167
Parent-wave observations	2091
C. Single and Cohabiting Mothers	
# of School Shootings	0.006
	(0.005)
Mean of Dep. Var.	0.0200
Parent-wave observations	3467

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : Units of observation are person by wave. The outcome is shown in the column heading. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. The sample is restricted to mothers which never leave their baseline state. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. *Child Receives Treatment for Depression* is an indicator variable that equals 1 if the child takes medication for depression, zero otherwise. For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.12: Effects of Exposure to School Shootings on Mothers' Mental Health and Life Satisfaction, Controlling for Violent Crime Rate

	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatis-fied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Mothers						
# of School Shootings	−0.001	−0.003	−0.005	0.007	−0.004	0.001
	(0.009)	(0.003)	(0.006)	(0.005)	(0.004)	(0.002)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	18875	18828	14656	14656	14656	14656
B. Married Mothers						
# of School Shootings	−0.025*	−0.000	−0.027***	0.022**	0.003	0.001
	(0.015)	(0.006)	(0.009)	(0.009)	(0.006)	(0.002)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	6604	6593	5305	5305	5305	5305
C. Single and Cohabiting Mothers						
# of School Shootings	0.011	−0.005	0.004	0.001	−0.007	0.002
	(0.011)	(0.004)	(0.007)	(0.006)	(0.005)	(0.003)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	12271	12235	9351	9351	9351	9351

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 6 separate regressions. Units of observation are person by wave. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for mothers of all family compositions: married, single, and cohabiting. Panel B shows results for married mothers and Panel C considers single and cohabiting mothers. Each regression controls for county violent crime rate (per 100 persons). For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.13: Effects of Exposure to School Shootings on Fathers' Mental Health and Life Satisfaction, Controlling for Violent Crime Rate

	Mental Health Index	Depressive Episode	Very Satisfied with Life	Somewhat Satisfied with Life	Somewhat Dissatis-fied with Life	Dissatisfied with Life
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Fathers						
# of School Shootings	−0.031*	0.010**	−0.006	0.007	−0.005	0.005*
	(0.016)	(0.005)	(0.006)	(0.007)	(0.003)	(0.002)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	10421	10420	7532	7532	7532	7532
B. Married Fathers						
# of School Shootings	−0.052***	0.009*	−0.036***	0.033**	0.001	0.001
	(0.016)	(0.005)	(0.014)	(0.013)	(0.004)	(0.003)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	4384	4384	3279	3279	3279	3279
C. Single and Cohabiting Fathers						
# of School Shootings	−0.016	0.010	0.013	−0.011	−0.010**	0.007
	(0.026)	(0.008)	(0.008)	(0.009)	(0.005)	(0.004)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	6037	6036	4253	4253	4253	4253

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 6 separate regressions. Units of observation are person by wave. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the father's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for fathers of all family compositions: married, single, and cohabiting. Panel B shows results for married fathers and Panel C considers single and cohabiting fathers. Each regression controls for county violent crime rate (per 100 persons). For regressions of Panel A, marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.14: Effects of Exposure to School Shootings on Children's Educational Expectations, Controlling for Violent Crime Rate

	Educational Expectation Index	Mother's Assessment of the Child's Llikelihood of Graduating College				Child's Assessment of the Llikelihood of Graduating College			
	Educational Expectation	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely	Very Likely	Somewhat Likely	Somewhat Unlikely	Very Unlikely
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Children of all Family Compositions									
# of School Shootings	−0.078*	−0.013	0.012	0.000	0.001	−0.067	0.064	0.007	−0.005
	(0.040)	(0.023)	(0.020)	(0.014)	(0.015)	(0.047)	(0.048)	(0.004)	(0.009)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	3099	3086	3086	3086	3086	2973	2973	2973	2973
B. Children Whose Mother is Married									
# of School Shootings	−0.174*	−0.028	0.010	0.003	0.015	−0.099*	0.117**	0.005	−0.023
	(0.090)	(0.035)	(0.035)	(0.012)	(0.025)	(0.049)	(0.050)	(0.004)	(0.017)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	1214	1209	1209	1209	1209	1171	1171	1171	1171
C. Children Whose Mother is Single or Cohabiting									
# of School Shootings	−0.009	−0.006	0.017	−0.002	−0.009	−0.037	0.020	0.009	0.008
	(0.067)	(0.038)	(0.027)	(0.019)	(0.017)	(0.051)	(0.050)	(0.007)	(0.005)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	1885	1877	1877	1877	1877	1802	1802	1802	1802

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.14: *(continued)* Effects of Exposure to School Shootings on Children's Educational Expectations, Controlling for Violent Crime Rate

	Children's Valuation of the Importance of Graduating College			Child's Perception of the Mother's Valuation of Graduating College		
	Very Important	Somewhat Important	Not Very Important	Very Important	Somewhat Important	Not Very Important
	(10)	(11)	(12)	(13)	(14)	(15)
A. Children of all Family Compositions						
# of School Shootings	−0.029	0.030*	−0.001	−0.015	0.005	0.010*
	(0.018)	(0.017)	(0.007)	(0.021)	(0.018)	(0.005)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	2976	2976	2976	2962	2962	2962
B. Children Whose Mother is Married						
# of School Shootings	−0.077*	0.071*	0.006	−0.065***	0.061**	0.003
	(0.037)	(0.041)	(0.018)	(0.022)	(0.022)	(0.003)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	1172	1172	1172	1167	1167	1167
C. Children Whose Mother is Single or Cohabiting						
# of School Shootings	0.008	−0.002	−0.006	0.021	−0.034	0.014
	(0.037)	(0.036)	(0.006)	(0.032)	(0.030)	(0.009)
Violent Crime Rate (per 100 persons)	Yes	Yes	Yes	Yes	Yes	Yes
Parent-wave observations	1804	1804	1804	1795	1795	1795

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 9 separate regressions. Units of observation are person by wave. Outcomes are shown in column headings. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. Each regression controls for county violent crime rate (per 100 persons). For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Table 1.15: Effects of Exposure to School Shootings on Children's Mental Health, Controlling for Violent Crime Rate

	Child Receives Treatment for Depression
A. Children of all Family Compositions	
# of School Shootings	0.006***
	(0.002)
Violent Crime Rate (per 100 persons)	Yes
Parent-wave observations	6547
B. Married Mothers	
# of School Shootings	0.008***
	(0.002)
Violent Crime Rate (per 100 persons)	Yes
Parent-wave observations	2531
C. Single and Cohabiting Mothers	
# of School Shootings	0.005*
	(0.002)
Violent Crime Rate (per 100 persons)	Yes
Parent-wave observations	4016

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : Units of observation are person by wave. The outcome is shown in the column heading. The table reports results from estimating the effects of school shooting exposure in the mother's baseline city of residence, where $\#ofSchoolShootings$ is a continuous variable indicating the number school shootings in the individual's city and wave that occur by the interview date of the following wave. Panel A presents results for children of all family compositions: mothers who are married, single, and cohabiting. Panel B shows results for children whose mother is married, and Panel C considers children whose mother is single and cohabiting. Each regression controls for county violent crime rate (per 100 persons). *Child Receives Treatment for Depression* is an indicator variable that equals 1 if the child takes medication for depression, zero otherwise. For regressions of Panel A, mother's marital status is also controlled. Robust standard errors are clustered on the city by wave level and are in parentheses.

Chapter 2

Wage Gap and Disability Types

Chapter Abstract

The challenges of adolescents with learning disabilities do not diminish as individuals mature in age, rather learning disabilities' effects extend into adulthood. When compared to the physically disabled and nondisabled, individuals with learning disabilities have the lowest educational attainment and subsequently fewer employment opportunities. Because the educational challenges faced by the learning disabled behave as a conduit to inferior employment outcomes, they contend with modest wages in conjunction with their disability. Using the National Education Longitudinal Study of 1988, I identify adolescents in the eighth grade who received services for disability types, learning and physical. Gender analysis reveals wage gaps between groups, wherein each estimation the learning disabled is the disadvantaged group. Wage regressions indicate that men with learning disabilities incur larger negative effects on log hourly wages due to learning disabilities than women. This research promotes the need for development of coping strategies that aid the learning disabled in higher educational attainment.

2.1 INTRODUCTION

Learning disabilities (LDs) hinder an individual from understanding and processing math, reading, writing, oral language, facial expressions, or body language. It is estimated that between 5 to 9 percent of the general population of the U.S. have a learning disability. Like physical disabilities (PDs), LDs do not dissipate as the individual ages; however, the severity of its effect become more prevalent in life outcome areas such as educational attainment, employment, marital status, and social relationships (Goldberg *et al.,* 2003; Morris *et al.,* 2009; Ettner, 2000; DeLeire, 2001). Although the effects of PDs on employment outcomes have been thoroughly examined, comparative analysis of PDs and LDs has not been explored.

In this paper, I use a nationally representative sample, National Education Longitudinal Study of 1988 (NELS88), to determine differences in wages, employment, and educational outcomes between PDs and LDs. The survey permits identification of adolescents in the 8th grade with learning and physical disabilities. The identified disabilities are permanent and do not weaken in degree over time. This research is of particular interest because of the significant portion of the U.S. population which have LDs and most often face challenges which are different from those with PDs and the nondisabled. Borkowski et. al., (1988), found that children/adolescents with LDs develop counterproductive traits which inhibit successful performance within educational settings. For the learning disabled, failing to acquire coping skills results in adverse adult life outcomes (Borkowski *et al.,* 1988; Deshler, 2005; Prior, 1996; Bryan, 2005).

As asserted by Dickinson and Verbeek (2002), very little attention has been given to investigating the labor outcomes of specific disabilities such as LDs (Dickinson & Verbeek, 2002). Using a unique but non representative dataset, they were the first to evaluate the wage gap between adults with and without LDs. The researchers found there to be a wage gap of US $3.50 for graduate students at the University of Arizona with learning disorders

when compared to the graduate students of the 1994 National Longitudinal Survey of Youth. Dickenson and Verbeek note the likely cause of the lack of research in this area is due to the paucity of publicly available data on the learning disabled. Furthermore, most data on the learning disabled do not facilitate exploration of life outcomes. This paper contributes to the literature through use of a representative longitudinal sample that permits study of those with LDs, PDs, and the nondisabled. The study follows a sample of children first surveyed in the 8th grade until they are approximately age 30, collecting educational attainment, marital status, and employment data. Using a sufficiently larger sample than Dickenson and Verbeek's research, I identify the raw wage gap between the *Nondisabled* and *Physically Disabled*, *Nondisabled* and *Learning Disabled*, and *Physically and Learning Disabled*, to be 0.86,1.77, and \$0.91 respectively.

To perform the study, the sample is categorized into one of three disability types, nondisabled, learning disabled, and physically disabled. The disability types are then separated by gender to form four groups, *Nondisabled and Disabled*, *Nondisabled and Learning Disabled*, *Nondisabled and Physically Disabled*, and *Physically and Learning Disabled*. The first objective of this paper is to examine whether the wages earned by people with LDs contrast significantly with wages of those with PDs and the nondisabled. I find that log hourly wages are significantly negatively influenced by LDs when compared to those with PDs and the nondisabled. Next, I explore gender differences in wages. The results of the wage regressions for groupings differed in the magnitudes of the marginal effects of disability types. LD yielded significant effect on log hourly wages for both genders in the pooled groups, *Nondisabled and Learning Disabled* and *Physical Disability and Learning Disability*. The model estimates indicate that men with learning disabilities incur larger negative effects on hourly wages than do women within these pooled groups.

Lastly, LDs often produce counterproductive traits in the individual such as low self-esteem, lack of motivation, and poor perspective of ability. I consider the channels which

contribute to the wage gap experienced by the learning disabled which may be influenced by these traits. The primary contributing channels considered are low educational attainment, unemployment, marriage, and full-time employment. Estimation from logistical analysis for men confirms that having a LD negatively affects the probability of earning a college degree; this finding bears statistical power. The results also show LDs decrease the likelihood of employment and working full-time; though these results are not significant, they facilitate the narrative that LDs can adversely affect life outcomes. Logistical regressions for women yield similar findings. For women, LDs are shown to have a negative relationship with the probability of marriage but analogous to the men's findings, only LDs negative influence on the probability of achieving a college degree holds significance.

The remainder of the paper is structured as follow. Section 2.2 discusses the data. Sections 2.3 and 2.4 present empirical method applied to sample groupings and discussion of data and analysis of results, respectively. Section 2.5 concludes the paper.

2.2 DATA

2.2.1 National Education Longitudinal Study of 1988

The data for this study is sourced from the base year and fourth follow-up period of the National Education Longitudinal Study of 1988. In 1988, NELS88 surveyed eighth graders and their parents and teachers. In the base year, demographic, health, and educational data were collected. During a twelve-year span which concluded in year 2000, the students were surveyed four times following the base year period. The first through third follow-up periods occurred every two years, with the third follow-up in year 1994. The fourth follow-up occurred six years later, when most students were 30 years of age. This follow-up gathered employment, wage, marital status, and post-secondary data. Approximately 25,000 students of a nationally representative sample were initially surveyed, but only 12,144 were

re-interviewed for the fourth follow-up. Other data which may be useful for this research are restricted due to the sensitive nature of disability content; nonetheless, NELS88 is the most current longitudinal dataset which contains the data necessary to conduct such research and is available to the public.

To determine whether a student had a learning disability, parents were asked if their child received services for a specific learning disability. Examples listed on the survey included dyslexia, reading, writing, math, and spelling disability. Parents were also asked if their child received services for a visual, deafness, orthopedic, or other physical disability. Responses to these questions were used to identify both the learning and physically disabled. Note that such disabilities do not dissipate nor are fully corrected with medical treatments; therefore, both the learning and physically disabled must learn coping strategies to manage their disabilities.

Disability type, GPA, mother's highest level of education, and region were captured during the student's eighth grade year. Students were asked to indicate the type of letter grades they usually earned in school. The grades were then assigned to a 4-point scale to create a GPA score. Employment, wage, current health, and education data were gathered during the fourth follow-up period. lnWage is the respondent's log hourly wage as of year 2000. The wage was constructed by dividing the weekly employment income by number of hours worked. Health Problem, a dummy variable, indicates whether the respondent incurred a health issue in year 2000 which limited the type and amount of work they did. Tenure indicates the length of time the respondent has worked for his/her current employer and is reported in number of years. Experience identifies, in years, the respondent's work experience. Other dummy variables include full-time, industry, and occupation. Industry and occupational categorial variables are determined by North American Industry Classification System (SAICS) and Standard Occupational Classification System, respectively. Because education variables were recorded prior to the realization of wage in year 2000, this infers

that respondents' educational attainment is not in response to wage but rather the opposite. Therefore, no issues arise due to reverse causality (Heckman *et al.,* 2006). Also, reporting bias is a noted concern in labor outcomes of persons with disabilities. This bias stems from the incentive of the disabled person to justify their employment status by exaggerating their health status (Bound *et al.,* 1995). However, for this paper, the respondents' disability status is determined from services received while in the 8th grade, so reporting bias is not a concern for estimation results of this paper.

2.2.2 Summary Statistics

Tables 2.1 and 2.2 display the descriptive statistics for each sample group. The sample is composed of 2,868 females and 2,978 males, of which, 437 students have a learning disability and 172 have a physical disability. The sample's racial make-up is consistent with population composition having 4,229 White, 462 Black, and 627 Hispanic individuals.

The table displays the mean of each variable by group and gender. From this table it is shown that the men's nondisabled group incurred the highest mean log hourly wage of 2.64 followed by the men's PDs group with a mean of 2.66.[1] The women's learning disabled group has the lowest mean log hourly wage of 2.21. What can be gleaned from the summary statistics is that the learning disabled, on average, incur the lowest hourly wage, GPA, least educational achievements, and are male.

2.3 METHODOLOGY

Linear equations are employed to estimate wages as a function of disability, demographic, and employment variables (Rosen, 1974) Regressions are estimated separately by gender, male and female, to compare disability effects on wages (Rosen, 1974). Three types of individuals will be considered per gender: nondisabled, learning disabled, and physically disabled. The

[1]The hourly wage is nominal; it reflects year 2000 prices.

structural wage function is as follows for each individual i, with disability type d:

$$lnW_{i,d} = \beta_0 + \beta_1 X_{i,d} + \epsilon_{i,d} \tag{2.1}$$

where:

$$d = N, L, P \tag{2.2}$$

$lnWage$ is natural log hourly wages for each individual i, where X is the matrix of individual observed variables, β_1 is the vector of corresponding coefficients, d identifies the disability type where N is no disability, L is learning disability, and P is physical disability.

Matrix X encompasses respondents' personal characteristics, marital status, number of dependents, GPA, work experience, tenure, region, and mother's educational attainment.

Inherent in wage regression analysis is the concern of selection bias. Because wage analysis only captures respondents with earnings, the analysis does not observe nonlabor force participants. Consequently, their potential earnings are not considered which could bias estimation results. Use of a fixed effects or sibling comparison can be employed to circumvent this issue; however, NELS88 data does not permit such analysis. Despite data limitations, a logistic regressions are used to determine the likelihood of employment, full-time status, educational attainment, and marriage by disability types.

LOGIT MODEL:

$$y_i = \begin{cases} 1, \text{if } i \text{ is employed} \\ 0, \text{if } i \text{ is unemployed} \end{cases} \tag{2.3}$$

$$Pr(y_{i,d}) = 1 = \frac{e^{x'_{i,d}\beta}}{1 + e^{x'_{i,d}\beta}} \tag{2.4}$$

$$Pr(y_{i,d}) = 0 = \frac{1}{1 + e^{x'_{i,d}\beta}} \tag{2.5}$$

Similar regressions are applied to dependent variables: *Full-Time, College Degree, and Married*. Where X is the matrix of individual observed variables and β_1 is the vector of corresponding coefficients. The explanatory variables of X used in the wage regression analysis are used in the logistic regression except for *More Than One Job, Full-Time, industry*, and occupation variables. The logistic regression estimates display the mean marginal effect on the probability of employment by each covariate. Logistic regressions are estimated by gender.

2.4 RESULTS

In Table 2.3 the first pooled grouping is *Nondisabled and Disabled*, where disabled is composed of both LDs and PDs. The second and third grouping compare the nondisabled to a disabled group, either LDs or PDs. The final grouping is composed of those with PDs and LDs only. The results unearth the raw wage effect of disabilities on log hourly wages in regressions 1, 3, 5, and 7; each are negative and significant. This indicates that absent any control variables, there are significant disparities in wages due to disabilities. Regressions 2, 4, 6, and 8 include control variables which aid in explaining wage differences in each grouping.

The estimated negative effects of LDs on log hourly wages in regressions 6 and 8 are strongly significant. PD, though negative, is not significant in final specification of the *Nondisabled and Physically Disabled* group. Furthermore, the variable, *Male*, signals significant positive effects on log hourly wages for men, indicating a wage gap between genders. These findings give way to the gender wage analysis provided in Tables 2.4-2.7. The regression estimates are used as a baseline for comparison with groups separated by gender.

2.4.1 Nondisabled and Disabled

In this analysis for each gender, like Table 2.3, both LDs and PDs compose the disability group and are pooled with the nondisabled. However, the first and fifth columns *lnWage* regression result in Table 2.4 display the raw effect of learning and physical disabilities on log hourly wages by for each gender. For men, the raw effect *Disability* is -0.11, while the estimate for women is notably greater in magnitude, -0.206. The effects of *Disability* vary in magnitude as control variables are added to each regression but remain negative and significant. The second regression result for men and women, columns 2 and 6, provide insight into contributions of demographic variables, race, age, mother's education, region, marital status, and number of dependents. The inclusion of demographic variables slightly reduces, in absolute terms, the marginal effect of *Disability* and shows significance of race and mother's education to wage.

The marginal effect of *Disability* in columns 3 and 7 considerably decrease in magnitude for both men and women, -0.079 and -0.113, respectively. The regressions consist of employment variables: *Tenure, Full-Time, more Than One Job, Health Problem, Experience, Industry, and Occupation.* Their explanatory powers diminish the penalty of *Disability* on hourly wages. Regressions 4 and 8, the preferred model, encompasses all variables. For men, *Disability* increases marginally, in absolute terms, to -0.082 and remains significant at the 0.05 percent level; while for women, *Disability* decreases, in absolute terms, to -0.093 but is significant at the 0.05 percent level as well. For women, *Dependents* bears a negative and significant effect on hourly wages; however, for men, this effect is positive, but not significant. *Full-Time and Experience* are also rewarded differently for each gender.

2.4.2 Nondisabled and Learning Disabled

In this analysis only the learning disabled and nondisabled are considered. In Table 2.5 the first *lnWage* regression for men includes only the dummy variable, *Learning Disability*, which captures the raw effect of LDs on log hourly wages. For men, the LDs coefficient varies little between the range of -0.147 to -0.12 as explanatory variables are added to the wage regression and remains statistically significant for all regression specifications at the 1 percent level. Women experience a larger spread in the effect of LDs. LDs diminish both in magnitude and significance in progression to the preferred estimation model, -0.241 to -0.111; nonetheless, LDs bear significance at the 1 percent level in the final specification.

2.4.3 Nondisabled and Physically Disabled

Table 2.6 displays results of the pooled group *Nondisabled and Physically Disabled*. The dummy variable, *Physical Disability*, indicates individuals with physical disabilities such as visual, deafness, and orthopedic. Column 4 reveals a positive effect of PDs on hourly wages for men; however, the variable bears no significance. For women, though negative, it is insignificant in the preferred model.

2.4.4 Physically and Learning Disabled

Further variation is unearthed in the men's pooled group, *Physically Disabled and Learning Disabled*, the group revealed insignificance of most explanatory variables. This presents the possibility that other covariates, not included in this regression analysis may play a more significant role in explaining hourly wages. In this regression analysis, the pooled group consists of both disability types, PDs and LDs. The marginal effect of LDs is -0.165 for men and is significant at the .1 level when all controls are added. Overall, the effects of LDs are larger, in absolute terms, for men. The disability variable also yields negative effects on the wages of women but carries no significance in full model. See Table 2.7 for results.

2.4.5 Logistic Regressions: Men

Table 2.8 displays the logistic results of *Employment, Full-Time, College Degree, and Married* for men. The results of the logistic regression in column 1 indicate that having a learning disability decreases the probability of employment. Therefore, if those who are unemployed and have a learning disability were to earn hourly wages, their hourly wages in all likelihood would be below the average log hourly wage of both the physically disabled and nondisabled, thus further increasing the wage gap. Estimation results are displayed in Table 2.8.

The estimations predict the mean marginal effect of LDs and PDs on male employment to be -0.002 and 0.019, respectively. This indicates that LDs decrease the probability of employment, while PDs increase the likelihood of employment. However, neither disability estimate is significant. Still, the logistic predictions corroborate wage results. By predicting a higher probability of employment for PDs, this implies more earning opportunities which would widen the wage gap experienced between the two groups. Therefore, the results of the log hourly wage regressions are likely to be conservative.[2] Logistic results of full-time employment yield similar results. Upon estimating the mean marginal effects of disabilities on obtaining a college degree for men, LDs are predicted to have negative effects and is significant at the 5 percent level. This reveals the potential for education to operate as an intermediate variable between LDs and hourly wages. Consequently, low educational achievement is the plausible explanation of the wage gap experienced by the learning disabled.

The marital status logistic analysis signals that PDs decrease the probability of marriage. Though this estimate is significant, the inclusion of variable, *Married*, into the wage model specification does not disconcert the results of this study. This finding may marginally narrow the wage gap experienced by the learning disabled when compared to those with PDs.

[2]Note: dy/dx for factor levels is the discrete change from the base level.

2.4.6 Logistic Regressions:Women

Table 2.9 displays the logistic results for women. The probability of employment, shown in column 1, is decreased by LDs but is increased for those with PDs; for PDs the estimate is significant. Again, this indicates that the spread in log hourly wages between the learning and physically disabled is likely wider than originally considered. Columns 2 and 4 show that the probability of *Full-Time and Married* are decreased by both LDs and PDs, but are not significant. Coefficient estimates of LDs and PDs are predicted to return negative effects on the probability of women earning college degrees. The LDs estimate is significant.

2.5 CONCLUSION

Though much research has examined the wage disparity of the disabled, few have estimated the wage gap by disability type (Fletcher, 2014; DeLeire, 2000). This study estimates the gender log wage gap experienced by those with learning disabilities. Using NELS88 data, I identify adolescents in the eighth grade who received services for learning disabilities such as reading, writing, and math. Because learning disabilities cannot be fully corrected through coping strategies, it seemed of interest to determine what effect, if any, learning disability bears on hourly wages. Wage regressions reveal significant negative marginal effects on log hourly wages due to learning disability. Having identified the raw nominal wage gap of the learning disabled for men and women to be \$1.95 and \$3.01, respectively, when compared to the nondisabled, I utilized wage regressions to estimate the effect of learning disability on wages and compared results to the effects of physical disabilities. Though women experience a larger nominal wage gap, the model estimates indicate that men with learning disabilities incur larger negative effects on log hourly wages due to LDs than do women within *Nondisabled and Learning Disabled and Physically and Learning Disabled* groups. Unlike the effects of LDs, PD is not significant for either gender in the pooled grouping, *Nondisabled and Physically Disabled*.

This analysis provides insight into the mechanisms which contribute to the modest wages of disabled groups, particularly the learning disabled. I estimate the associations between LDs and college degree, employment, and worked full-time. It is shown that LDs decrease the probability that both genders will earn a college degree. Because education is a channel which supports employment outcomes, LDs effect on the probability of achieving higher education is likely to present challenges with securing employment and full-time status. Also, not having a college degree can reduce one's potential earnings. Investigating the employment outcomes of the learning disabled, which make up approximately 5 to 9% of the U.S. population, brings to light the challenges they face in addition to their disability. Developing methods that will close the gap in educational attainment as well as wages can potentially diminish the difficulties of the learning disabled.

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2.6 TABLES

Table 2.1: Mean Summary Statistics by Group

	Men			Women		
Variable	Mean Nondisabled	Mean Learning	Mean Physical	Mean Nondisabled	Mean Learning	Mean Physical
Hourly Wage[2]	16.54	14.59	16.78	13.70	10.69	10.62
lnWage	2.639	2.491	2.664	2.449	2.208	2.248
Age	29.627	29.301	29.5	29.731	29.452	29.476
Black	.071	.039	.067	.094	.032	.098
Hispanic	.107	.082	.078	.113	.077	.098
Other non-White	.093	.078	.078	.092	.065	.073
White	.73	.801	.778	.701	.826	.732
Mother's Education						
Dropout	.119	.124	.1	.172	.226	.159
High School	.387	.372	.367	.365	.452	.39
Some Postsecondary	.205	.238	.167	.236	.142	.232
College Degree	.289	.266	.367	.227	.181	.22
Dropout	.032	.064	.022	.024	.065	.012
High School	.166	.277	.222	.13	.329	.28
Some Postsecondary	.448	.493	.456	.467	.458	.415
College Degree	.354	.167	.3	.379	.148	.293
Married	.358	.429	.244	.432	.394	.354
Dependents	.447	.67	.411	.615	.787	.659
GPA	2.993	2.471	2.742	3.112	2.572	3.026
Tenure	2.713	3.092	2.544	2.346	2.451	2.39
Full Time	.915	.929	.9	.851	.761	.732
> Than One Job	.126	.131	.167	.12	.09	.061
Experience	4.04	4.068	4.041	3.962	3.908	3.826
Health Problem	.018	.053	.078	.023	.077	.073
Midwest	.293	.34	.411	.292	.323	.317
South	.339	.33	.267	.352	.239	.317
West	.191	.138	.156	.174	.2	.183
Northeast	.177	.191	.167	.182	.239	.183
	Obs. 2625	*Obs. 282*	*Obs. 90*	*Obs. 2649*	*Obs. 172*	*Obs. 82*

Table 2.2: Industry Mean Summary Statistics by Group

	Men			Women		
Variable	Mean Nondisabled	Mean Learning	Mean Physical	Mean Nondisabled	Mean Learning	Mean Physical
Agriculture	.02	.028	.011	.008	.006	.024
Mining	.008	.007	.011	.001	0	0
Construction	.109	.163	.111	.017	.013	.012
Manufacturing	.171	.177	.156	.092	.09	.037
Transportation	.096	.074	.089	.077	.019	.049
Wholesale Trade	.026	.039	.011	.013	.019	0
Retail Trade	.21	.17	.278	.238	.206	.207
Finance	.077	.067	.067	.104	.09	.085
Services	.231	.216	.211	.429	.529	.561
Public Administration	.051	.057	.056	.02	.026	.024
Management	.153	.128	.133	.137	.11	.098
Business & Financial	.216	.191	.156	.421	.335	.378
Computer	.09	.064	.1	.039	.006	.037
Engineering	.06	.028	.011	.017	.019	.024
Social Service	.04	.014	.033	.089	.206	.146
Education	.026	.021	.033	.051	.039	.012
Arts & Entertainment	.106	.117	.133	.038	.019	.024
Healthcare	.024	.018	.033	.12	.135	.134
Protective Service	.02	.014	.033	.013	0	.012
Food	.008	.021	0	.007	.013	.012
Agriculture	.015	.021	.011	.003	0	0
Maintenance	.128	.184	.144	.029	.052	.037
Military	.017	.011	.011	.007	0	0
Laborers	.098	.167	.167	.031	.065	.085
	Obs. 2625	*Obs. 282*	*Obs. 90*	*Obs. 2649*	*Obs. 172*	*Obs. 82*

Table 2.3: Regression Results of Group: Nondisabled and Disabled

	Nondisabled and Disabled		*Nondisabled and Physically Disabled*		*Nondisabled and Learning Disabled*		*Physically and Learning Disabled*	
	(1) *lnWage*	(2) *lnWage*	(3) *lnWage*	(4) *lnWage*	(5) *lnWage*	(6) *lnWage*	(7) *lnWage*	(8) *lnWage*
Disability	-.124***	-.087***	-.078*	-.029	-.153***	-.117***		
	(.027)	(.026)	(.047)	(.044)	(.03)	(.029)		
Learning Disability							-.128**	-.134**
							(.059)	(.057)
Male		.145***		.147***		.143***		.217***
		(.017)		(.017)		(.017)		(.059)
Black		-.078***		-.074**		-.078***		-.1
		(.029)		(.03)		(.03)		(.113)
Hispanic		-.01		-.004		-.009		-.119
		(.026)		(.027)		(.027)		(.092)
Other Nonwhite		.02		.026		.024		-.121
		(.027)		(.027)		(.027)		(.09)
Age		-.324		.227		-.367		-2.067
		(1.184)		(1.26)		(1.204)		(3.166)
Age^2		.006		-.003		.007		.037
		(.02)		(.021)		(.02)		(.054)
Mother's Edu.								
Dropout		-.176***		-.178***		-.18***		-.129
		(.027)		(.028)		(.027)		(.082)
High School		-.075***		-.08***		-.076***		-.04
		(.02)		(.021)		(.021)		(.064)
College Degree		.065***		.062***		.066***		.038
		(.022)		(.023)		(.022)		(.07)
Married		.032*		.038**		.032*		-.073
		(.016)		(.017)		(.017)		(.054)
Dependents		-.036***		-.04***		-.036***		-.001
		(.009)		(.01)		(.01)		(.029)
Tenure		.047***		.044***		.049***		.052*
		(.009)		(.01)		(.01)		(.03)
$Tenure^2$		-.004***		-.003***		-.004***		-.004
		(.001)		(.001)		(.001)		(.003)
Full Time		.178***		.192***		.183***		-.038
		(.024)		(.025)		(.025)		(.072)
>Than One Job		-.016		-.02		-.018		.012
		(.023)		(.024)		(.023)		(.075)
Health Problem		-.153***		-.165***		-.146***		-.284***
		(.048)		(.052)		(.05)		(.096)
Experience		.046***		.045***		.043***		.124***
		(.013)		(.014)		(.014)		(.042)
_cons	2.544***	5.802	2.544***	-2.284	2.544***	6.43	2.511***	30.797
	(.008)	(17.374)	(.008)	(18.51)	(.008)	(17.672)	(.052)	(46.228)
Observations	5846	5846	5446	5446	5711	5711	609	609
R-squared	.004	.145	.001	.145	.004	.144	.008	.22
Region	NO	YES	NO	YES	NO	YES	NO	YES
Industry	NO	YES	NO	YES	NO	YES	NO	YES
Occupation	NO	YES	NO	YES	NO	YES	NO	YES

Standard errors are in parentheses *** $p<.01$, ** $p<.05$, * $p<.1$

Table 2.4: Regression Results of Group by Gender: Nondisabled and Disabled

	MEN				WOMEN			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnWage	*lnWage*	*lnWage*	*lnWage*	*lnWage*	*lnWage*	*lnWage*	*lnWage*
Disability	-.11***	-.104***	-.079**	-.082**	-.206***	-.157***	-.113***	-.093**
	(.034)	(.035)	(.033)	(.033)	(.042)	(.041)	(.04)	(.04)
Black		-.131***		-.112**		-.044		-.042
		(.046)		(.044)		(.04)		(.038)
Hispanic		-.095**		-.08**		.096**		.071*
		(.038)		(.037)		(.038)		(.037)
Other Nonwhite		-.031		-.041		.064*		.069*
		(.04)		(.038)		(.038)		(.037)
Age		-.582		-.71		1.732		.929
		(1.634)		(1.561)		(1.879)		(1.82)
Age^2		.011		.013		-.028		-.014
		(.028)		(.027)		(.032)		(.031)
Mother's Edu.								
Dropout		-.093**		-.103**		-.23***		-.22***
		(.042)		(.04)		(.036)		(.035)
High School		-.03		-.038		-.122***		-.107***
		(.03)		(.029)		(.028)		(.028)
College Degree		.112***		.082***		.027		.036
		(.032)		(.031)		(.032)		(.031)
Married		.063**		.028		.019		.006
		(.026)		(.025)		(.023)		(.022)
Dependents		.003		.016		-.106***		-.076***
		(.015)		(.015)		(.012)		(.013)
Tenure			.062***	.059***			.033**	.032**
			(.013)	(.013)			(.014)	(.014)
$Tenure^2$			-.005***	-.005***			-.003**	-.002
			(.001)	(.001)			(.002)	(.002)
Full Time			.239***	.237***			.141***	.126***
			(.04)	(.04)			(.031)	(.03)
> Than One Job			-.083***	-.07**			.031	.025
			(.032)	(.032)			(.033)	(.033)
Health Problem			-.076	-.07			-.253***	-.23***
			(.071)	(.071)			(.066)	(.065)
Experience			.051**	.055***			.06***	.021
			(.02)	(.02)			(.018)	(.018)
_cons	2.639***	10.429	1.803***	11.696	2.449***	-24.111	1.553***	-12.878
	(.012)	(23.954)	(.111)	(22.902)	(.012)	(27.609)	(.125)	(26.754)
Observations	2978	2978	2978	2978	2868	2868	2868	2868
R-squared	.003	.03	.117	.134	.008	.093	.107	.163
Region	NO	YES	NO	YES	NO	YES	NO	YES
Industry	NO	NO	YES	YES	NO	NO	YES	YES
Occupation	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors are in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

Table 2.5: Regression Results of Group by Gender: Nondisabled and Learning Disabled

	MEN				WOMEN			
	(1) *lnWage*	(2) *lnWage*	(3) *lnWage*	(4) *lnWage*	(5) *lnWage*	(6) *lnWage*	(7) *lnWage*	(8) *lnWage*
Learning Disability	-.147***	-.141***	-.12***	-.124***	-.241***	-.176***	-.145***	-.111**
	(.038)	(.038)	(.037)	(.037)	(.049)	(.048)	(.048)	(.047)
Black		-.126***		-.109**		-.05		-.048
		(.046)		(.044)		(.04)		(.039)
Hispanic		-.095**		-.079**		.1***		.074**
		(.039)		(.037)		(.038)		(.037)
Other Nonwhite		-.026		-.037		.064*		.07*
		(.04)		(.038)		(.039)		(.038)
Age		-.664		-.817		1.803		1.098
		(1.656)		(1.581)		(1.92)		(1.864)
Age^2		.012		.014		-.029		-.017
		(.028)		(.027)		(.033)		(.032)
Mother's Edu.								
Dropout		-.102**		-.112***		-.23***		-.22***
		(.042)		(.041)		(.037)		(.036)
High School		-.03		-.04		-.126***		-.109***
		(.031)		(.03)		(.029)		(.028)
College Degree		.119***		.089***		.023		.03
		(.032)		(.031)		(.032)		(.032)
Married		.066**		.029		.018		.005
		(.026)		(.025)		(.023)		(.022)
Dependents		.007		.019		-.107***		-.078***
		(.015)		(.015)		(.013)		(.013)
Tenure			.065***	.062***			.034**	.032**
			(.013)	(.013)			(.014)	(.014)
$Tenure^2$			-.005***	-.005***			-.003**	-.002
			(.001)	(.001)			(.002)	(.002)
Full Time			.25***	.249***			.142***	.124***
			(.04)	(.04)			(.031)	(.031)
>Than One Job			-.09***	-.075**			.032	.024
			(.033)	(.032)			(.034)	(.033)
Health Problem			-.059	-.051			-.259***	-.231***
			(.074)	(.074)			(.068)	(.067)
Experience			.046**	.051**			.06***	.019
			(.02)	(.02)			(.018)	(.018)
_cons	2.639***	11.678	1.803***	13.297	2.449***	-25.187	1.544***	-15.403
	(.012)	(24.285)	(.112)	(23.188)	(.012)	(28.227)	(.129)	(27.405)
Observations	2907	2907	2907	2907	2804	2804	2804	2804
R-squared	.005	.033	.12	.138	.008	.093	.104	.161
Region	NO	YES	NO	YES	NO	YES	NO	YES
Industry	NO	NO	YES	YES	NO	NO	YES	YES
Occupation	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors are in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

Table 2.6: Regression Results of Group by Gender: Nondisabled and Physically Disabled

	MEN				WOMEN			
	(1) *lnWage*	(2) *lnWage*	(3) *lnWage*	(4) *lnWage*	(5) *lnWage*	(6) *lnWage*	(7) *lnWage*	(8) *lnWage*
Physical Disability	.025	.025	.066	.059	-.201***	-.167***	-.104	-.098
	(.065)	(.064)	(.062)	(.061)	(.067)	(.064)	(.064)	(.063)
Black		-.129***		-.11**		-.042		-.044
		(.047)		(.045)		(.04)		(.039)
Hispanic		-.088**		-.076**		.101***		.071*
		(.04)		(.038)		(.038)		(.037)
Other Nonwhite		-.026		-.035		.072*		.074*
		(.041)		(.039)		(.039)		(.038)
Age		.154		-.101		2.209		1.233
		(1.771)		(1.689)		(1.952)		(1.891)
Age^2		-.002		.002		-.036		-.02
		(.03)		(.029)		(.033)		(.032)
Mother's Edu.								
Dropout		-.1**		-.112***		-.226***		-.215***
		(.044)		(.043)		(.037)		(.036)
High School		-.041		-.05		-.117***		-.102***
		(.032)		(.031)		(.029)		(.028)
College Degree		.1***		.07**		.035		.045
		(.033)		(.032)		(.032)		(.032)
Married		.084***		.047*		.015		.002
		(.027)		(.026)		(.023)		(.023)
Dependents		-.005		.007		-.105***		-.074***
		(.016)		(.015)		(.013)		(.013)
Tenure			.061***	.059***			.026*	.026*
			(.014)	(.014)			(.014)	(.014)
$Tenure^2$			-.005***	-.005***			-.003	-.002
			(.002)	(.002)			(.002)	(.002)
Full Time			.254***	.249***			.158***	.148***
			(.041)	(.041)			(.032)	(.031)
>Than One Job			-.097***	-.083**			.032	.03
			(.033)	(.033)			(.034)	(.033)
Health Problem			-.093	-.084			-.268***	-.237***
			(.079)	(.078)			(.071)	(.069)
Experience			.055***	.058***			.056***	.017
			(.021)	(.021)			(.019)	(.019)
_cons	2.639***	-.337	1.793***	2.808	2.449***	-31.144	1.52***	-17.424
	(.012)	(25.986)	(.116)	(24.791)	(.012)	(28.697)	(.132)	(27.799)
Observations	2715	2715	2715	2715	2731	2731	2731	2731
R-squared	0	.028	.118	.136	.003	.088	.103	.16
Region	NO	YES	NO	YES	NO	YES	NO	YES
Industry	NO	NO	YES	YES	NO	NO	YES	YES
Occupation	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors are in parentheses
*** *p<.01, ** p<.05, * p<.1*

Table 2.7: Regression Results of Group by Gender: Physically and Learning Disabled

	MEN				WOMEN			
	(1) *lnWage*	(2) *lnWage*	(3) *lnWage*	(4) *lnWage*	(5) *lnWage*	(6) *lnWage*	(7) *lnWage*	(8) *lnWage*
Learning Disability	-.177**	-.151*	-.201**	-.165*	-.146*	-.068	-.124	-.065
	(.08)	(.082)	(.082)	(.085)	(.082)	(.08)	(.078)	(.079)
Black		-.224		-.178		.086		.13
		(.158)		(.165)		(.159)		(.16)
Hispanic		-.186		-.156		-.099		.027
		(.122)		(.127)		(.138)		(.14)
Other Nonwhite		-.162		-.186		-.088		.012
		(.12)		(.123)		(.138)		(.14)
Age		-5.989		-5.965		2.908		1.026
		(4.211)		(4.302)		(4.999)		(4.964)
Age^2		.104		.103		-.048		-.016
		(.072)		(.074)		(.086)		(.085)
Mother's Edu.								
Dropout		-.035		-.06		-.316***		-.303***
		(.116)		(.121)		(.118)		(.115)
High School		.045		.057		-.251**		-.218**
		(.086)		(.089)		(.1)		(.098)
College Degree		.089		.047		-.034		-.002
		(.09)		(.096)		(.114)		(.112)
Married		-.073		-.126		.038		.071
		(.076)		(.08)		(.078)		(.076)
Dependents		.044		.066		-.121***		-.084*
		(.041)		(.043)		(.04)		(.043)
Tenure			.037	.027			.111***	.078*
			(.042)	(.043)			(.042)	(.045)
$Tenure^2$			-.003	-.002			-.011**	-.007
			(.005)	(.005)			(.005)	(.005)
Full Time			-.078	-.079			-.05	-.08
			(.126)	(.128)			(.085)	(.087)
>Than One Job			.014	.016			-.08	-.071
			(.095)	(.097)			(.128)	(.129)
Health Problem			-.229*	-.254*			-.358***	-.355***
			(.136)	(.139)			(.134)	(.133)
Experience			.09	.101			.151***	.133**
			(.062)	(.065)			(.055)	(.056)
_cons	2.676***	88.853	2.257***	88.051	2.329***	-41.628	1.748***	-13.831
	(.072)	(61.481)	(.31)	(62.834)	(.07)	(72.946)	(.302)	(72.504)
Observations	372	372	372	372	237	237	237	237
R-squared	.013	.047	.108	.147	.013	.194	.295	.382
Region	NO	YES	NO	YES	NO	YES	NO	YES
Industry	NO	NO	YES	YES	NO	NO	YES	YES
Occupation	NO	NO	YES	YES	NO	NO	YES	YES

Standard errors are in parentheses
*** $p<.01$, ** $p<.05$, * $p<.1$

Table 2.8: Logit Regressions of Nondisabled and Disabled: MEN

	Employment dy/dx	Full Time dy/dx	College Degree dy/dx	Married dy/dx
Learning Disability	-0.002	-0.005	-0.057	0.008
	(0.010)	(0.019)	(0.028)	(0.034)
Physical Disability	0.019	0.018	0.004	-0.112
	(0.010)	(0.027)	(0.050)	(0.048)
Black	-0.020	-0.021	-0.050	-0.228
	(0.013)	(0.021)	(0.030)	(0.023)
Hispanic	0.006	-0.017	-0.066	-0.083
	(0.008)	(0.019)	(0.026)	(0.029)
Other Nonwhite	-0.006	-0.013	0.005	-0.115
	(0.009)	(0.018)	(0.029)	(0.029)
Age	0.195	0.389	0.665	2.052
	(0.377)	(0.768)	(1.614)	(1.391)
Age^2	-0.003	-0.007	-0.010	-0.036
	(0.006)	(0.013)	(0.027)	(0.024)
Mother's Edu.				
Dropout	-0.020	-0.006	-0.129	-0.044
	(0.012)	(0.019)	(0.024)	(0.030)
Some Postsecondary	-0.004	-0.010	0.068	-0.031
	(0.008)	(0.015)	(0.024)	(0.025)
College Degree	-0.002	0.004	0.206	-0.056
	(0.007)	(0.013)	(0.024)	(0.023)
Married	0.017	0.067	0.016	
	(0.006)	(0.011)	(0.020)	
Dependents	-0.004	0.010	-0.169	0.260
	(0.004)	(0.008)	(0.016)	(0.014)
GPA	-0.010	-0.016	0.252	0.016
	(0.004)	(0.008)	(0.015)	(0.014)
Tenure	-0.016	0.014	0.000	0.045
	(0.003)	(0.006)	(0.012)	(0.011)
$Tenure^2$	0.001	-0.001	-0.005	-0.004
	(0.000)	(0.001)	(0.002)	(0.001)
Health Problem	-0.013	-0.026	-0.067	-0.098
	(0.020)	(0.035)	(0.044)	(0.054)
Full Time			0.095	0.152
			(0.019)	(0.026)
Experience	0.061	0.115	-0.105	0.037
	(0.005)	(0.007)	(0.015)	(0.017)
Midwest	0.001	-0.005	-0.095	0.065
	(0.008)	(0.015)	(0.020)	(0.030)
South	-0.005	-0.005	-0.119	0.135
	(0.008)	(0.015)	(0.020)	(0.029)
West	-0.014	-0.020	-0.140	0.084
	(0.010)	(0.018)	(0.019)	(0.034)

Table 2.9: Logit Regressions of Nondisabled and Disabled: WOMEN

	Employment dy/dx	Full Time dy/dx	College Degree dy/dx	Married dy/dx
Learning Disability	-0.016	-0.061	-0.057	-0.019
	(0.022)	(0.038)	(0.028)	(0.039)
Physical Disability	0.040	-0.049	0.004	-0.076
	(0.020)	(0.053)	(0.050)	(0.053)
Black	0.018	0.051	-0.050	-0.341
	(0.015)	(0.027)	(0.030)	(0.021)
Hispanic	-0.009	0.008	-0.066	-0.090
	(0.017)	(0.027)	(0.026)	(0.029)
Other Nonwhite	-0.014	-0.021	0.005	-0.095
	(0.018)	(0.029)	(0.029)	(0.030)
Age	0.973	1.476	0.665	3.339
	(0.750)	(1.293)	(1.614)	(1.579)
Age^2	-0.016	-0.025	-0.010	-0.057
	(0.013)	(0.022)	(0.027)	(0.027)
Mother's Edu.				
Dropout	0.039	0.075	-0.129	-0.008
	(0.011)	(0.021)	(0.024)	(0.027)
Some Postsecondary	0.020	0.044	0.068	0.018
	(0.012)	(0.020)	(0.024)	(0.024)
College Degree	0.008	0.016	0.206	-0.048
	(0.013)	(0.022)	(0.024)	(0.024)
Married	-0.028	-0.083	0.016	
	(0.010)	(0.017)	(0.020)	
Dependents	-0.010	-0.033	-0.169	0.135
	(0.005)	(0.009)	(0.016)	(0.011)
GPA	0.012	0.005	0.252	0.056
	(0.007)	(0.012)	(0.015)	(0.014)
Tenure	-0.057	0.001	0.000	0.050
	(0.007)	(0.010)	(0.012)	(0.012)
$Tenure^2$	0.004	-0.002	-0.005	-0.003
	(0.001)	(0.001)	(0.002)	(0.001)
Health Problem	0.004	-0.022	-0.067	-0.093
	(0.027)	(0.049)	(0.044)	(0.052)
Full Time			0.095	-0.111
			(0.019)	(0.023)
Experience	0.153	0.254	-0.105	0.006
	(0.008)	(0.012)	(0.015)	(0.013)
Midwest	-0.020	-0.004	-0.095	0.090
	(0.016)	(0.024)	(0.020)	(0.027)
South	-0.008	0.011	-0.119	0.166
	(0.015)	(0.024)	(0.020)	(0.026)
West	-0.045	-0.073	-0.140	0.070
	(0.021)	(0.030)	(0.019)	(0.031)

Chapter 3

Can I Blame It On Mom? The Relationship Between Parental Mental Health and Adolescent Risky Behavior

Chapter Abstract

Millions of parents in the United States suffer with depression. However, parental depression is not isolated to the individual, but spills over into the family unit. Adolescents may be especially vulnerable to parental depression because adolescence is a key transitional period into adulthood. It is during this time adolescents began to explore boundaries and establish behavior. Parental depression stands to adversely affect the behavior of adolescents through negative parenting and lack of emotional support. This paper examines the associative differences in adolescent risky behavior due to the timing and onset of parental depression. My results show that history of maternal depression and recency of depressive episode is positively correlated with adolescent risky behavior. Specifically, I find that recency of maternal depression, when the child is 15 years of age has greater correlation than the mother's overall history of depression to adolescent risky behavior. Also, I find that recency of pater-

nal depression is correlated with a 14.5 percentage point decrease in GPA of adolescents; a stronger correlation to GPA than maternal depression. Considering how parental depression impedes healthy development in adolescence is imperative to understanding the behavior in adulthood and provides a basis for potential policy interventions in regard to adolescent development.

3.1 INTRODUCTION

Adolescence is viewed as a significant period of transition into adulthood. It is during the adolescent period that an individual discovers sexuality, establishes self-control, develops neurologically and emotionally, and learns cognitive reasoning (Yurgelun-Todd, 2007). Researchers have richly explored the effects and associations of adverse events on adolescent outcomes and found that poor adolescent development can lead to economic disadvantage in adulthood such as low educational attainment, poor health, and increased likelihood of criminal activity (Yoshikawa *et al.,* 2012; Coley *et al.,* 2017; Ruhm, 2008; Trzesniewski *et al.,* 2006; Jackson, 2009; Gruber, 2009). However, little is known about the relationship between parental depression and adolescent risky behavior. Exploring how family factors impede healthy development in adolescence is imperative to understanding the behavior in adulthood and provides a basis for potential policy interventions in regard to adolescent development. This paper fills this gap in literature by examining the relationship between the timing and onset of poor parental mental health on adolescent risky behavior.

Depression affects the mental and emotional health of an individual. Furthermore, depression does not "turn off" but rather the intensity of the illness varies over time (Colman & Ataullahhan, 2010). Because of this, the effects of parental depression in early childhood are more likely to generate persistent outcomes in adolescent behavior than parental depression experienced only as an adolescent (Johnston *et al.,* 2013). Still, the spillover from poor parental mental health may adversely influence the risky behavior of adolescents through maltreatment, neglect, and lack of emotional support (Mustillo *et al.,* 2011; Council *et al.,* 2009).

Parental depression in early childhood is linked to adverse behavioral development in children. Turney (2011), using wave 3 of the Fragile Families and Childwellbeing Study, examined the association of the recency and degree of maternal depression with behavioral

and cognitive outcomes of children. Turney (2011) finds that children with mothers experiencing chronic depression are more likely to have behavior problems than children whose mother does not experience chronic depression, and the magnitude increases if the mother is currently depressed. Additionally, other researchers have found similar results which reveal that poor parental mental health is associated with lower cognitive development in children (Mensah & Kiernan, 2009; Meadows *et al.,* 2007).

Researchers agree that poor parental mental health can serve as a pathway to poor mental health and adult labor market outcomes of adolescents (Wolicki *et al.,* 2021; Johnston *et al.,* 2013). Using the 1970 British Cohort Study, Johnston *et al.* (2013) show that the mothers' mental health is intergenerationally persistent and significantly correlated with the mental health of the children. The researchers find that poor intergenerational persistent maternal mental health bears negative lasting effects on children's adult labor market outcomes. Their research reveals that a one-standard-deviation increase in the average maternal mental health, is associated with a 16-percentage point increase in the average mental health of a youth. The researchers also show that a one-standard-deviation decrease in the maternal mental health is associated with a 1.4% decrease in the probability that the youth will earn a college degree and decreases the youth's adult log household income by 3.6%.

I estimate the relationship between the timing and onset of poor parental mental health and adolescent behavior by ordinary least squares and linear probability models. I use the longitudinal data set, Fragile Families and Child Wellbeing Study, which oversamples unwed parents and follows both parents and child for six waves. By measuring depression at each wave for each parent, I am able to determine whether adolescent outcomes differ by timing of parental depression as well as the depressed parent's gender.

My research reveals that the associations due to timing and onset of parental depression differs by parental gender. The results show that maternal depression history and recency of depressive episode is positively correlated with adolescent risky behavior. Also, I provide

evidence of the lingering effects of paternal depression on adolescent risky behavior. I find that recency of paternal depression is correlated with a 14.5 percentage point decrease in GPA of adolescents; a stronger correlation to GPA than maternal depression.[1]

This paper makes three primary contributions to the literature. First, prior literature evaluates the effects of "recent" or "ever experienced" parental depression on children and adolescent mental health outcomes (Johnston *et al.,* 2013; Turney, 2011; Mensah & Kiernan, 2009; Meadows *et al.,* 2007; Vallotton *et al.,* 2016; Conway & Kennedy, 2004; Dahlen, 2016). The effects of parental depression in early childhood include lower child birth weight, reduction in children's test scores, and poorer health outcomes for the child (Conway & Kennedy, 2004; Dahlen, 2016; Propper *et al.,* 2007). Studies which evaluate the effects of parental depression on adolescents find that adolescents are more likely to have depressive episodes and less life optimism (Johnson *et al.,* 2018; Hardie & Turney, 2022). Though the findings of previous research suggest that parental depression yields adverse effects on the mental health of adolescents, I extend this literature by examining the differences in adolescent risky behavior due to the timing and onset of parental depression. Second, few studies examine the relationship of paternal mental health and youth outcomes. This is largely due to data limitations because few data sets follow both parents and focal child as the child ages. I overcome this limitation by using the Fragile Families and Childwellbeing Study (FFCWS); a study which conducts interviews with both parents, whether the father lives in residence with child or is a nonresident father. It is important to consider whether the impact of fathers' mental health yields different results on the risky behavior of adolescents than mothers. Third, using the FFCWS data set researchers have evaluated associations between parental depression and children's behavioral outcomes. However, to the best of my knowledge, no researcher has used this data set to evaluate the relationship between the timing of parental mental health and adolescent risky behavior. My research reveals this relationship and broadens the understanding of parental depression.

[1] Results are relative to the mean.

The remainder of this paper is organized as follows: Section 3.2 discusses the data. Section 3.3 introduces the empirical specification. Section 3.4 presents the results and robustness checks. Lastly section 3.5 concludes.

3.2 DATA

3.2.1 Fragile Families and Childwellbeing Study

To analyze the relationship between adolescent risky behavior and parental depression I use the publicly available data from the Fragile Families and Childwellbeing Study (FFCWS) from 1998-2017. The data, which is an oversampling of unwed parents, comprises approximately 5000 families from 20 United States metropolitan cities. FFCWS follows the families for six waves which correspond to the child's age: birth, 1, 3, 5, and 15.[2] Once the child became 9 years old, the child was also interviewed along with both parents. At the age 15 interview, only the primary caregiver and the child are interviewed.[3] These data contain detailed information on the families' health and heath behavior, attitudes and expectations, education, family history, and family dynamics.

The analytic sample is limited to parents which participated in each survey wave.[4] This accordingly determines the number of adolescents in sample. For this reason, the sample includes 2,271 mothers and 1,286 fathers.

Due to the nature of the data, there is the concern of selection bias. Selection bias causes bias estimates due to a poor representative sample. Groups may choose not to participate in the FFCWS because of internal factors, such as mental health and this would result in bias estimates. However, if an individual chooses not to participate in the sample due to poor mental health, it is likely that the coefficient estimates of my study are below the true

[2] At the time of this research, only data for waves 1-6 are available.

[3] 93% of primary caregivers are mothers. Consequently, the analyses include data on fathers for waves 1-5.

[4] Fathers are only assessed for waves 1-6.

parameter. To determine whether selection bias influences the results of my study, I use a logit regression to perform a robustness check on the likelihood that poor mental health is associated with survey participation. I find that poor mental health does help to explain a mother's decision to participate in FFCWS but is not associated with a father's survey participation decision. The results are shown in Table 3.12.

3.2.2 Summary Statistics

As shown in Figure 3.1, 11% of mothers experience depression at child's age 1 and this percent increases to 19% at child's age 15. Mean paternal depression at child age 1 is 8% and increases marginally at child age 15 to 9.3%, displayed in Figure 3.2. Table 3.1 provides the sample means and standard deviations of all variables used in my analyses. Approximately 43% of the fathers in the sample are nonresident fathers.[5] Fifty percent of the focal children are Black, 24% Hispanic, and 22% White. Approximately 50% of the focal children are boys. Among mothers in the FFCWS, the highest educational attainment for 17% is "less than high school", 18% have high school diploma, and 45% have "some college". My study makes use of data from waves 1-6 for mothers, and waves 1-5 for fathers.

3.3 EMPIRICAL DESIGN

My goal is to estimate the correlation between parental mental health and the adolescent risky behavior of their children. To do so, I use an ordinary least squares and linear probability models. Specifically, I estimate the following model for each individual i, at wave w:

$$Y_{i,w} = \beta_0 + \beta_1 ParentalDepression_{i,w} + \beta_2 X_{i,w} + \gamma_w + u_{i,w} \tag{3.1}$$

$Y_{i,w}$ is an outcome of interest, such as the adolescents grade point average. $ParentalDepression$ is the key explanatory variable, which is an indicator variable equal to 1 if the parent expe-

[5] A nonresident father is a father who does not live in the same home as the focal child.

riences a major depressive episode in that wave, and 0 otherwise. An additional measure of parental depression included in some regression analysis is a binary variable identifying if the parent ever experienced depression in any wave. $X_{i,w}$ is a vector of parental and adolescent characteristics that comprise indicator for nonresident father (equal to 1 if father does not live in same residence as adolescent, and 0 otherwise), parental race/ethnicity (Black, Hispanic, White, other), parental education (less than high school, high school diploma, some college, bachelor's degree or higher), parental age (15-25, 26-35, 36-45, 46-55, and 55+) , indicator for parental employment status (equal to 1 if parent is employed in that wave, and 0 otherwise), parent poverty level ratio, child's age, child's age squared, indicator for child takes medication for depression (equal to 1 if child takes medication for depression, and 0 otherwise), indicator for breast fed (equal to 1 if child was breast fed, and 0 otherwise), and indicator for low birth weight (equal to 1 if child had low birth weight, and 0 otherwise). γ_{cw} captures wave fixed effects (i.e., an indicator for each of the six wave cells), accounting for all time-invariant and time-varying differences that may take place in any given wave. The key coefficient of interest β_1, which measures the relationship between the onset of parental depression and the risky behavior outcomes of interest measured at wave 6. Standard errors are clustered at the level of variation, individual by wave (note, there are 2,271 clusters for maternal analysis and 1,286 clusters for paternal analysis).

I use the linear probability estimation to model the probability of binary outcomes of interest because it permits clear interpretation of coefficients. Unlike a fixed effects logit specification, the linear probability model retains all parents for analysis: parents who experience no depression in any wave and parents who experience depression in all waves, as well as parents which experience a change in their depression status. However, there is the potential for unobserved heterogeneity. This means that individual specific unobserved factors may contribute to the relationship between parental depression and adolescent risky behavior. Consequently, the true parameter β_1 may be smaller in magnitude if unobserved heterogeneity, such as child's outlook on life, has a greater impact on adolescent risky behavior than

parental depression. However, it is likely that the child's heterogeneous characteristics will indirectly affect the parent's mental health causing a family mental health spillover.

Current literature examines the relationship between maternal depression and the mental health of their children, but few studies investigate the associations between fathers' mental health and children's mental health. Furthermore, few studies estimate how the timing of parental depression may generate differing outcomes in children. I am interested in examining whether the timing of maternal depression affects adolescent risky behavior differently paternal depression. To do this, I estimate equation (1), separately for mothers and fathers. I study several outcomes that are sourced from the youth's wave 6 interview. Youth's risky behavior outcomes which consists of binary indicators equal to 1 if (1) youth uses illegal drugs and (2) youth uses opioids, (3) youth skips school, (4) youth has been suspended or expelled within the last 2 years, and (5) a continuous variable which measures the youth's GPA at wave 6.

A limitation of this study is that there is a limited sample of fathers interviewed at wave 6; consequently, fathers are only included in the analysis during waves 1-5. Also, because adolescent outcomes are only asked in wave 6, my empirical specification cannot account for heterogeneity of individuals. As a result, it may be that unobserved individual characteristics may help to explain the relationship between paternal depression and adolescent behavior.

3.4 RESULTS

Tables 3.2-3.3 present my main results on the associations between the timing and onset of poor maternal mental health and adolescent risky behaviors. The adolescent behavioral outcome of Table 3.2 is likelihood of illegal drug usage, which is a binary indicator equal to 1 if the youth indicated drug usage, and 0 otherwise. Illegal drug usage includes marijuana, hallucinogen, cocaine/crack, heroin, methamphetamine, cold medication, ecstasy, glue, and other drug usage. As shown in column 1, a one unit increase in the mother's overall history

of depression, increases the likelihood of adolescent usage of illegal drugs by 3.4 percentage points and is significant at the .05 level. A stronger correlation is found when mother's depression is only considered at youth's age of 9 and 15. In column (7), I find that maternal depression experienced when the youth is age 15 remains persistent at 4 percentage points, even controlling for prior waves of depression. A similar pattern of results is found in Table 3.3, where the outcome variable is likelihood of opioid usage. Opioid usage is a binary indicator variable equal to 1 if youth indicated opioid usage, and 0 otherwise. Opioid usage comprises prescription amphetamines/uppers, painkillers, sedatives/tranquilizers, and other prescription drugs. Column (1) of Table 3.3 shows that a one unit increase in the mother's overall history of depression, increases the likelihood of adolescent opioid usage by 1.4 percentage points. Though significant at the 10% level, maternal depression at the youth's age 15 bears similar correlational magnitude. However, in comparison of the magnitude of mother's overall history of depression and maternal depression at youth's age 9, the latter increases the likelihood of opioid usage in adolescence at a larger magnitude.

Tables 3.4-3.6 present the main results on the correlation between the timing and onset of poor maternal mental health and adolescent risky behavior. Table 3.4 shows the association between maternal depression and the adolescent's likelihood of suspension/expulsion. Both the mother's overall history of depression and maternal depression experienced at youth's age of 15 increases the adolescent's likelihood of suspension/expulsion. However, maternal history of depression and maternal depression at adolescent's age 15, together, are insignificant. This is shown in column (8). Table 3.5 shows results for the adolescent's likelihood of skipping school. Neither the overall maternal depression history nor maternal depression experienced at any youth age yield significant association to this outcome. Table 3.6 displays results for the associations between the timing and onset of maternal depression and the adolescent's grade point average at wave 6. GPA is a continuous variable with a minimum value of 1 and a maximum value of 4. The values are oriented so that higher values are favorable. Maternal depression at specific ages is not significant, but rather the mother's

overall mental health history is significant to the adolescent's GPA. A one unit increase in the mother's depression history, decreases the adolescent's GPA by 5 percentage points.

Paternal depression is identified in waves 2-5 because only the primary caregiver of the focal child is interviewed in wave six, and 93% of the sample's primary caregivers are mothers. Results on the relationships between the timing and onset of poor paternal mental health and adolescent risky behavior are shown in Tables 3.7-3.8. Table 3.7 estimates the relationship between paternal depression history and paternal depression at specific youth ages. Though depression coefficients are positive, paternal depression does not bear any significant correlation with the adolescent's likelihood of illegal drug usage. The same result is found in Table 3.8 where likelihood of opioid usage is the dependent variable.

I show in Tables 3.9-3.11 results of the correlation between the timing and onset of paternal depression and adolescent risky behavior. As shown in Tables 3.9 and 3.10, paternal depression is not correlated with adolescent school suspension/expulsion nor the likelihood that the adolescent skips school. A different pattern emerges in Table 3.11 where the outcome GPA. Though negative, paternal depression history does not have a significant correlation with adolescent's GPA; however, as shown in columns (2), (6), and (7) paternal depression at youth's age 9 has a strong negative correlation with the adolescent's GPA at age 15. A one unit increase in paternal depression at youth's age 9 decreases the adolescent's GPA by 13.6 to 14.5 percentage points relative to the mean.

3.4.1 Robustness Check

Table 3.12 show the results of the logit regression which estimates the relationship between survey participation and parental depression. Column (1) shows that a marginal increase in maternal depression decreases the likelihood of a mother's survey participation by 16.2%. As shown in column (2), an increase in paternal depression does not significantly explain a father's decision to participate in the survey.

3.5 DISCUSSION

Adolescents may be especially vulnerable to parental depression because adolescence is a key transitional period into adulthood. It is during this time individuals become self-aware and form habits which may be long-term. The choices made my adolescents have been shown to have long-term effects (Gruber, 2009). Considering how parental depression impedes healthy development in adolescence is imperative to understanding the behavior in adulthood and provides a basis for potential policy interventions in regard to adolescent development.

My research reveals that timing and onset of parental depression differs by parental gender. This is consistent with studies which evaluate children's' behavioral changes due to maternal depression (Meadows *et al.,* 2007; Turney, 2011). The results show that maternal depression history and recency of depressive episode is positively correlated with adolescent risky behavior. Specifically, I find that recency of maternal depression, when the child is 15 years of age, has greater correlation than the mother's overall history of depression to adolescent risky behavior. Though maternal depression experienced at child ages 1, 3, and 5 are not significantly correlated to risky behavior in adolescence, these depressive episodes are present within the maternal history of depression.

Due to data limitations, previous literature has not estimated relationships between paternal depression and adolescent outcomes. However, using the unique data, FFCWS, I have provided evidence of the lingering effects of paternal depression on adolescent risky behavior. I find that recency of paternal depression is correlated with a 14.5 percentage point decrease in GPA of adolescents; a stronger correlation to GPA than maternal depression.

As previously mentioned, a limitation of this study is that there is a limited sample of fathers interviewed at wave 6; consequently, fathers are only included in the analysis during waves 1-5. For that reason, it is likely that the coefficient estimates for fathers are below the true effect.

The robustness check reveals that maternal depression is adversely related to likelihood of survey participation. This implies that the sample is affected by selection bias, so the results of this study should be carefully considered. Nonetheless, a mother's decision to abstain from survey participation due to poor mental health suggests that the coefficient estimates of my study are below the true parameter. If all mothers with poor mental health participate in the survey, it is likely my coefficient estimates would be greater in magnitude and achieve more statistical power.

3.6 CONCLUSION

The period of adolescence is a pivotal point in the transition into adulthood. Most often during this time of transition, adolescents' greatest source of support are their parents. Yet for many youths, their parents struggle with depression. Parents experiencing depression may find it difficult to provide emotional support or may adopt a hostile parenting style. Thus inducing the youth to form unhealthy habits and behaviors to cope with the unfavorable living environment. The decisions by adolescents to engage in risky behavior such as drug and opioid usage and criminal activity can have far reaching effects into adulthood.

My research shows that timing and onset of parental depression differs by parental gender. Maternal depression history and recency of depressive episode is strongly correlated with adolescent risky behavior. This means that worsening maternal mental health is correlated to increases in the likelihood of adolescent risky behavior. Also, I have provided evidence of the lingering effects of paternal depression on adolescent risky behavior. Future research is needed to understand what channels of parental depression influence correlation between parental mental health and adolescent risky behavior.

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3.7 TABLES AND FIGURES

Figure 3.1: Mean Maternal Depression at Child Ages 1-15

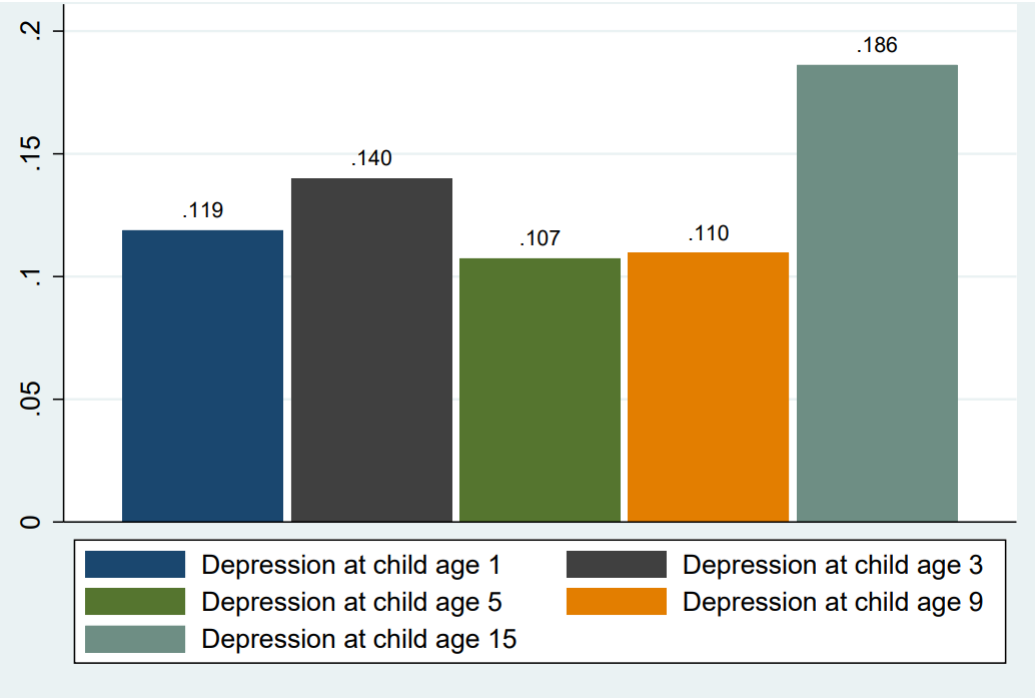

Figure 3.2: Mean Paternal Depression at Child Ages 1-9

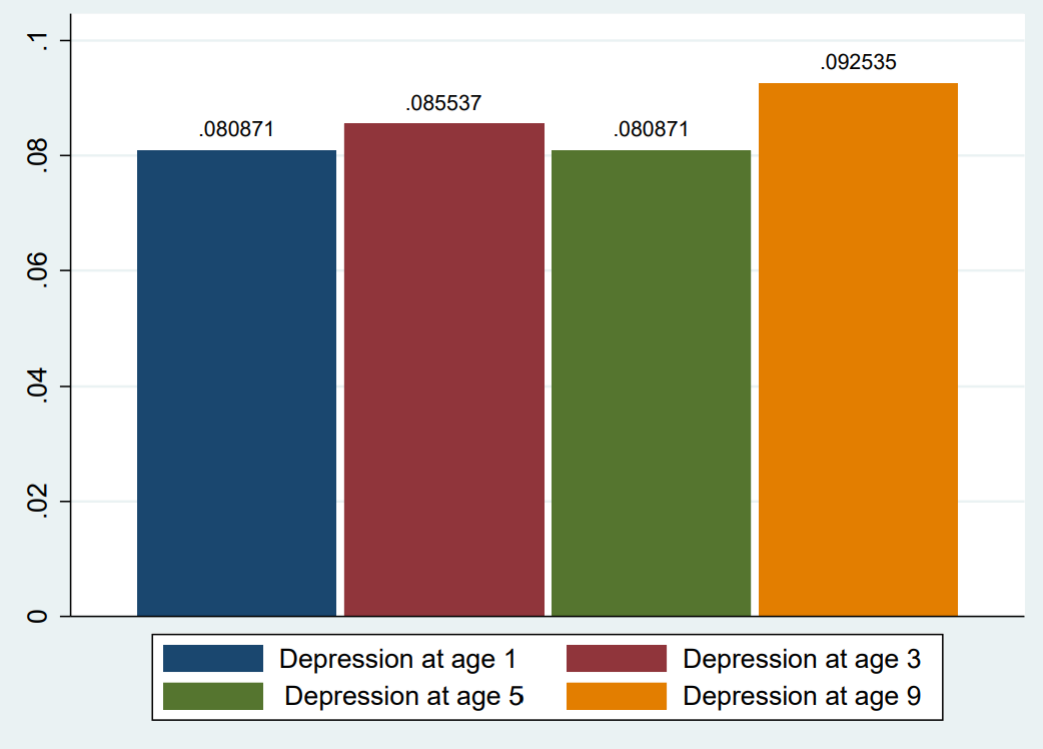

Table 3.1: Summary Statistics by Parental Gender

	Mothers	Fathers
Ever Depressed	0.384	0.219
	(0.486)	(0.413)
Number of waves depressed	0.662	0.340
	(1.053)	(0.743)
Nonresident Father	0.546	0.433
	(0.498)	(0.496)
Black	0.504	0.470
	(0.500)	(0.499)
Hispanic	0.237	0.235
	(0.425)	(0.424)
White	0.221	0.255
	(0.415)	(0.436)
Other ethnicity	0.038	0.040
	(0.192)	(0.197)
Age	30.22	43.86
	(7.863)	(7.130)
Less than high school	0.165	
	(0.371)	
High school diploma	0.179	
	(0.384)	
Some college	0.448	
	(0.497)	
BA or higher	0.208	
	(0.406)	
Child's age	15.507	
	(.619)	
Child is a boy	0.503	
	(0.500)	
Child was breast fed	0.586	
	(0.493)	
Child had low birth weight	0.089	
	(0.285)	
Child receives treatment for depression	0.029	
	(0.167)	
Individual-wave observations	2271	1286

Table 3.2: Maternal Depression on Child's Likelihood of Illegal Drug Usage at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother Depressed								
Ever Depressed	0.034**							0.018
	(0.015)							(0.018)
At child age 15		0.046**					0.040*	0.033
		(0.020)					(0.022)	(0.024)
At child age 9			0.045*				0.034	
			(0.025)				(0.028)	
At child age 5				0.011			−0.010	
				(0.024)			(0.025)	
At child age 3					0.029		0.022	
					(0.022)		(0.023)	
At child age 1						−0.015	−0.031	
						(0.022)	(0.023)	
Mean of Dep. Var.	0.126							
	(0.332)							
Individual-wave observations	2271	2271	2271	2271	2271	2271	2271	2271

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 8 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor maternal mental health where mother's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. $MotherEverDepressed$ is a binary indicator equal to 1 if mother is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.3: Maternal Depression on Child's Likelihood of Opioid Usage at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother Depressed								
Ever Depressed	0.014**							0.011
	(0.006)							(0.008)
At child age 15		0.014*					0.011	0.007
		(0.009)					(0.010)	(0.011)
At child age 9			0.021*				0.018	
			(0.012)				(0.013)	
At child age 5				0.013			0.007	
				(0.011)			(0.011)	
At child age 3					0.003		−0.005	
					(0.008)		(0.008)	
At child age 1						0.001	−0.003	
						(0.008)	(0.008)	
Mean of Dep. Var.	0.016							
	(0.125)							
Individual-wave observations	2271	2271	2271	2271	2271	2271	2271	2271

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 8 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor maternal mental health where mother's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. $MotherEverDepressed$ is a binary indicator equal to 1 if mother is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.4: Maternal Depression on Child's Likelihood of Suspension/Expulsion at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother Depressed								
Ever Depressed	0.049***							0.035
	(0.018)							(0.023)
At child age 15		0.055**					0.050**	0.030
		(0.023)					(0.025)	(0.029)
At child age 9			0.014				−0.010	
			(0.029)				(0.030)	
At child age 5				0.031			0.009	
				(0.030)			(0.032)	
At child age 3					0.029		0.007	
					(0.026)		(0.028)	
At child age 1						0.046	0.035	
						(0.028)	(0.030)	
Mean of Dep. Var.	0.233							
	(0.423)							
Individual-wave observations	2271	2271	2271	2271	2271	2271	2271	2271

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 8 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor maternal mental health where mother's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. $MotherEverDepressed$ is a binary indicator equal to 1 if mother is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.5: Maternal Depression on Child's Likelihood of Skipping School at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother Depressed								
Ever Depressed	0.000							−0.004
	(0.015)							(0.018)
At child age 15		0.006					0.005	0.009
		(0.018)					(0.019)	(0.022)
At child age 9			0.022				0.024	
			(0.024)				(0.025)	
At child age 5				0.005			0.004	
				(0.023)			(0.025)	
At child age 3					−0.000		0.002	
					(0.020)		(0.023)	
At child age 1						−0.031	−0.036*	
						(0.020)	(0.022)	
Mean of Dep. Var.	0.20							
	(0.325)							
Individual-wave observations	2271	2271	2271	2271	2271	2271	2271	2271

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 8 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor maternal mental health where mother's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. $MotherEverDepressed$ is a binary indicator equal to 1 if mother is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.6: Maternal Depression on Child's GPA at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mother Depressed								
Ever Depressed	−0.050*							−0.055
	(0.028)							(0.036)
At child age 15		−0.030					−0.014	0.010
		(0.034)					(0.037)	(0.044)
At child age 9			−0.044				−0.027	
			(0.045)				(0.048)	
At child age 5				−0.035			−0.011	
				(0.047)			(0.051)	
At child age 3					−0.046		−0.030	
					(0.038)		(0.041)	
At child age 1						−0.032	−0.015	
						(0.044)	(0.046)	
At child age 1						−0.032	−0.013	
						(0.044)	(0.046)	
Mean of Dep. Var.	2.873							
	(0.669)							
Individual-wave observations	2271	2271	2271	2271	2271	2271	2271	2271

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 8 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor maternal mental health where mother's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. $MotherEverDepressed$ is a binary indicator equal to 1 if mother is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.7: Paternal Depression on Child's Likelihood of Illegal Drug Usage at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father Depressed							
Ever Depressed	0.021						−0.004
	(0.022)						(0.026)
At child age 9		0.057				0.055	0.060
		(0.035)				(0.037)	(0.042)
At child age 5			0.017			0.010	
			(0.033)			(0.036)	
At child age 3				0.028		0.017	
				(0.035)		(0.038)	
At child age 1					−0.005	−0.025	
					(0.032)	(0.036)	
Mean of Dep. Var.	0.103						
	(0.304)						
Individual-wave observations	1286	1286	1286	1286	1286	1286	1286

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor paternal mental health where father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. *FatherEverDepressed* is a binary indicator equal to 1 if father is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.8: Paternal Depression on Child's Likelihood of Opioid Usage at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father Depressed							
Ever Depressed	0.007						−0.000
	(0.011)						(0.012)
At child age 9		0.018				0.016	0.018
		(0.017)				(0.017)	(0.020)
At child age 5			−0.001			−0.010	
			(0.014)			(0.014)	
At child age 3				0.008		0.001	
				(0.016)		(0.018)	
At child age 1					0.020	0.019	
					(0.019)	(0.020)	
Mean of Dep. Var.	0.018						
	(0.133)						
Individual-wave observations	1286	1286	1286	1286	1286	1286	1286

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor paternal mental health where father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. *FatherEverDepressed* is a binary indicator equal to 1 if father is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.9: Paternal Depression on Child's Likelihood of Suspension/Expulsion at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father Depressed							
Ever Depressed	0.046						0.030
	(0.028)						(0.034)
At child age 9		0.063				0.060	0.037
		(0.041)				(0.044)	(0.050)
At child age 5			0.051			0.040	
			(0.042)			(0.045)	
At child age 3				−0.001		−0.035	
				(0.037)		(0.041)	
At child age 1					0.043	0.029	
					(0.043)	(0.048)	
Mean of Dep. Var.	0.191						
	(0.393)						
Individual-wave observations	1286	1286	1286	1286	1286	1286	1286

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor paternal mental health where father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. *FatherEverDepressed* is a binary indicator equal to 1 if father is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.10: Paternal Depression on Child's Likelihood of Skipping School at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father Depressed							
Ever Depressed	0.013						−0.006
	(0.024)						(0.028)
At child age 9		0.041				0.054	0.046
		(0.036)				(0.038)	(0.043)
At child age 5			0.001			0.009	
			(0.035)			(0.037)	
At child age 3				−0.017		−0.023	
				(0.032)		(0.036)	
At child age 1					−0.033	−0.041	
					(0.031)	(0.036)	
Mean of Dep. Var.	0.117						
	(0.321)						
Individual-wave observations	1286	1286	1286	1286	1286	1286	1286

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor paternal mental health where father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. *FatherEverDepressed* is a binary indicator equal to 1 if father is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.11: Paternal Depression on Child's GPA at Age 15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father Depressed							
Ever Depressed	−0.067						−0.011
	(0.044)						(0.049)
At child age 9		−0.145**				−0.138**	−0.136*
		(0.069)				(0.070)	(0.079)
At child age 5			−0.013			0.033	
			(0.063)			(0.067)	
At child age 3				−0.042		0.011	
				(0.064)		(0.070)	
At child age 1					−0.095	−0.078	
					(0.069)	(0.072)	
Mean of Dep. Var.	2.96						
	(0.669)						
Individual-wave observations	1286	1286	1286	1286	1286	1286	1286

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 7 separate regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between the timing and onset of poor paternal mental health where father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother is depressed and 0 otherwise. *FatherEverDepressed* is a binary indicator equal to 1 if father is ever depressed at any of youth's ages, and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.

Table 3.12: Parental Survey Participation

	Mother Survey Participation	Father Survey Participation
Mother Ever Depressed	-0.162^{***}	
	(0.008)	
Father Ever Depressed		-0.010
		(0.008)
Individual-wave observations	5239	3205

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes : This table reports regression coefficients from 2 separate logit regressions. Outcome is shown in column heading. The table reports results from estimating the relationship between survey participation and poor parental mental health where mother's and father's depression status at youth's specific ages is the key explanatory variable, which is a binary variable equal to 1 if the mother (father) is depressed and 0 otherwise. All regressions control for wave fixed effects (i.e., an indicator for each of the 6 wave cells), ten-year age bins for mothers and fathers (15-25, 26-35, 36-45, 46-55, and 55+), child's age , child's age squared, race (Black, Hispanic, White, Other), education level (less than high school, high school diploma, some college, four-year degree or higher), indicator for child gender, indicator for child receiving treatment for depression (equal to 1 if child receives treatment, 0 otherwise), binary indicator for low birth weight (equal to 1 if child had low birth weight, 0 otherwise), binary variable identifying if the child was breast fed (equal to 1 if child was breast fed, 0 otherwise), indicator for nonresident father (equal to 1 if father lives in same residence as the child, 0 otherwise), mother's poverty ratio, indicator for mother's employment status (equal to 1 if mother is employed, 0 otherwise) . Robust standard errors are clustered on the individual by wave level and are in parentheses.