STATE MENTAL HEALTH INSURANCE PARITY LAWS AND COLLEGE EDUCATIONAL OUTCOMES

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Abstract

In the U.S., mental illness is widespread. In 2016, 18.3 percent of American adults experienced some form of mental illness. However, the majority of individuals with mental illness do not receive any treatment. Historically, insurance coverage for mental healthcare has been less generous than general healthcare coverage. To address unequal treatment of mental healthcare coverage, numerous U.S. states have implemented laws that compel private insurers to cover mental healthcare services at 'parity' with general healthcare services. In this study, I examine the effect of the state-level full parity mental illness law implementation on mental illness among college-aged individuals and human capital accumulation in college. It is important to consider spill-overs to these educational outcomes, as previous research shows that mental illness impedes college performance. I utilize administrative data on completed suicides and grade point average, and survey data on reported mental illness days and decision to drop-out of college between 1998 and 2008 in differences-in-differences (DD) analysis to uncover causal effects of state-level parity laws. Following the passage of a state-level full parity law, I find that the suicide rate reduces, the propensity to report any poor mental health day reduces, college GPA increases, and the propensity to drop out of college does not change.

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1 Introduction

Mental illnesses are widespread worldwide, in both developed and developing countries (World Health Organization, 2018a). Moreover, mental illnesses account for a larger proportion of disability in developed countries than any other group of illnesses, including cancer and heart disease (Reeves et al., 2011). In the U.S., approximately one in five adults lives with mental illness. 18.3 percent of U.S. adults experienced some form of mental illness in 2016. Younger adults (ages 18 to 25 years) experience higher prevalence of mental illness (22.1 percent in 2016) compared to older adults (Substance Abuse and Mental Health Health Services Administration, 2017). Moreover, most mental illnesses develop during adolescence and early adulthood, and 75 percent of chronic mental illnesses begin by age 24 (Kessler, Demler, Frank, Olfson, Pincus, Walters, Wang, Wells and Zaslavsky, 2005; Kessler, Berglund, Demler, Jin, Merikangas and Walters, 2005). In the U.S., about 41 percent of young adults attend college (McFarland et al., 2018),[2] and mental illnesses are widespread among college students. For instance, in fall 2017, approximately 40 percent of college students reported that they experienced depressive symptoms which adversely affected their well-being in the last year (Ibrahim et al., 2013; American College Health Association, 2018b). For individuals in school, mental illnesses have adverse effects on their educational performances (Currie and Stabile, 2006; Cornaglia et al., 2015; Kessler et al., 1995; Bilodeau and Meissner, 2016). For example, Eisenberg et al. (2009) find that mental illnesses are negatively correlated with GPAs of college students. Further, individuals with mental illnesses face disproportionate barriers in attending school and finding employment, and are more likely to die prematurely (World Health Organization, 2018b).

The widespread presence of mental illnesses in the U.S. is troubling from a social policy perspective as social costs of these illnesses are incurred through decreased labor supply, increased public support payments, reduced educational attainment,

[2]The college participation rate, or the college enrollment rate, is defined as the percentage of 18- to 24-year-old (the traditional college-age population) enrolled in 2- or 4-year degree-granting postsecondary institutions.

declined life expectancy (a loss of 13 to 32 years), and increased costs associated with other consequences such as incarceration or homelessness (Insel, 2008). In particular, mental illnesses cost the U.S. economy \$519.5B in healthcare expenditures, disability payments, and a less productive work force (Insel, 2015).[3]

The private costs of mental healthcare services are non-trivial. The key barriers to receiving mental healthcare treatment are lack of insurance and inability to pay for treatment (Wang et al., 2002; Kessler, Demler, Frank, Olfson, Pincus, Walters, Wang, Wells and Zaslavsky, 2005). In particular, mental illness treatments are costly for an uninsured patient: mental healthcare provider reimbursement rates can range from \$67 to \$144 per visit (Mark et al., 2017). These costs place a greater burden on individuals who may require a continuum of treatments on their pathway to recovery from mental illness. Due to these barriers of treatment, despite the effectiveness of mental illness treatments, the majority of individuals with mental illnesses do not receive treatment. Moreover, Zivin et al. (2009) find that while the majority of students with probable mental illnesses are aware of the need for treatment, most of these students do not receive treatment. Indeed, in 2016, less than half of adults with mental illness had received any treatment within the past year (Substance Abuse and Mental Health Health Services Administration, 2017).

The demand for healthcare services model suggests that insurance reduces the out-of-pocket price of healthcare services, increasing the quantity of healthcare demanded (Grossman, 1972). Therefore, insurance coverage should increase the affordability of mental healthcare treatments and, in turn, increase utilization of these treatments. However, historically, in the U.S., private insurance coverage for mental illness treatments has been less generous than benefits for general medical treatments due to concerns about the large demand elasticity for mental healthcare services (McGuire and Montgomery, 1982). For example, benefits for mental healthcare commonly include higher cost-sharing, lower annual outpatient visit and inpatient day limits, and other non-quantiative means (e.g., use of prior authorization and stepped therapy)

[3] Using the Consumer Price Index, I inflated this estimate from the original figure (\$467B in 2012 dollars) to August 2018 dollars.

(Busch and Barry, 2008; U.S. General Accountability Office, 2000).

State mental illness parity laws were implemented in a number of states of the U.S, in the late 1990s and 2000s, to improve coverage of mental health services and increase access to mental health services. These laws require private insurance companies to include mental health benefits at the same terms and conditions as physical health benefits. Studies find that these laws have been effective in reducing the financial burden on families of children with mental healthcare needs, and increasing use of mental healthcare services (Busch and Barry, 2007, 2008). State mental illness parity laws also improve mental health. Lang (2013) finds that state-level suicide rate decreases by 5 percent when a state passes a state mental illness parity law.

My study extends the literature on state-level mental illness parity laws in several ways. I focus on younger adults, the population most likely to suffer from mental illnesses. I study the effect of state-level mental illness parity laws on mental illness among college-aged population, as the early onset of mental illnesses can result in a trajectory of adverse academic, occupational, health, and social outcomes. I examine the effects of state-level mental illness parity laws on educational outcomes of college students (grade point average and decision to drop out of school) as mental illnesses are widespread among college students and affect their thoughts, feelings, or moods. Understanding how mental illness parity laws affect human capital accumulation in college is vital for developing and maintaining a skilled workforce for the U.S. economy. In addition, academic success during college years affects future earnings, and other labor market outcomes. Thus, examining the effect of state mental illness parity laws on educational outcomes could show an important spillover from public health policy to the U.S. labor markets.

I use differences-in-differences (DD) models to uncover the causal effects of state-level full parity mental illness laws on mental illness and educational outcomes. I couple DD models with both administrative and survey data, and include state-level controls to account for between state heterogeneity. I leverage plausibly exogenous variation in private insurance coverage for mental healthcare using changes in state laws over the period 1998 to 2008. In particular, there were 24 law changes over this time period, which offer substantial variation for identification of DD models. This analysis proceeds in two steps. First, to study parity law effects on mental illness, I utilize administrative data on completed suicides from National Vital Statistics System and survey data on reported mental illness from Behavioral Risk Factor System. Second, I use longitudinal data from the National Longitudinal Survey of Youth 1997 Cohort to examine the effects of mental illness parity laws on two important educational outcomes: drop out decisions and grade point average (GPA).

I have four principle findings. (i) Passage of a state-level full parity mental illness law leads to reductions in poor mental health days and suicide among the college-aged population. Post-law the suicide rate decreases by 3.5 percent and the propensity to report any poor mental health day in the last 30 days reduces by 1.8 percentage points. (ii) Passage of a state-level full parity mental illness law increases academic performance among college students; post-law the annual average GPA increases by 0.110 GPA points. (iii) The GPA effects are concentrated among female students. This finding supports evidence that females with mental illnesses are more likely to receive treatment than males (Substance Abuse and Mental Health Services Administration, 2015). (iv) Passage of a state-level full parity mental illness law does not statistically significantly change the propensity to drop out of college. These results can inform policymaker decisions about mental healthcare insurance laws for young adults.

This manuscript proceeds as follows: Section 2 describes state-level mental illness parity laws, outlines the conceptual framework that motivates my analysis, and summarizes the related literature. Section 3 describes the data, variables, and methods. Section 4 presents the results, and Section 5 reports robustness checks and extensions. Section 6 concludes.

2 State mental illness parity laws, conceptual framework, and prior research

I next discuss the state mental illness insurance legislation, review a conceptual framework that motivates an economic study of state-level full parity mental illness laws on mental health outcomes and educational outcomes, and summarize the related literature on state mental illness parity laws on mental health outcomes.

2.1 Mental illness insurance legislation in private markets

Historically, in the U.S., private insurance coverage for mental healthcare benefits has been more limited than for general healthcare.[4] For example, Barry et al. (2003) find that 74 percent of employees with private insurance for mental healthcare coverage were subject to outpatient visit limits, 64 percent were subject to inpatient day limits, and 22 percent had higher cost-sharing for mental healthcare compared with other services. Federal and state governments have implemented laws to reduce this coverage inequality between mental and general healthcare.

The federal government has implemented three key coverage changes. In 1996, in order to help address the public health issue of inadequate mental illness treatment, the U.S. Congress passed the Mental Health Parity Act (MHPA), which became effective on January 1st 1998. Specifically, the law prohibits employers that offer mental healthcare from imposing annual or lifetime dollar limits on mental health coverage that are more restrictive than those imposed on medical and surgical coverage (U.S. General Accountability Office, 2000). In 2008, Congress passed the Mental Health Parity and Addiction Equity Act (MHPAEA), which became effective on January 1st 2010. MHPAEA prohibits employers that offer mental healthcare from imposing cost-sharing or treatment limits on mental health coverage that are more stringent than those imposed on general medical care. Both the MHPA and MHPAEA do not mandate that private health plans provide mental healthcare benefits, and the provisions of these Acts are only applicable to plans that provide mental health coverage. In 2010, Congress passed the Affordable Care Act (ACA), which became fully effective on January 1st 2014. The ACA lists mental healthcare services as one of the ten essential benefits that all health plans in small groups and policies in individual private insurance markets, as well as many public plans, must cover. This Act extended MHPAEA by requiring equality of coverage for mental illness treatment in all

[4] Public insurance coverage has been more restrictive as well.

affected plans instead of requiring parity only for health plans that provide mental healthcare coverage.

States also implemented laws to improve coverage of mental health services in the private insurance market. Following MHPA in 1996, a number of states passed their own mental health insurance laws, many of which are stronger regulations than MHPA.[5] However, prior to 1996, 11 states had some type of mental illness insurance law implemented (Lang, 2013). These state parity laws were implemented to increase access to mental health services. State laws define mental illness differently, and there is heterogeneity in the strength of state laws. States with full parity mental illness laws mandate that mental health coverage be included in health insurance packages, and they require equality in all respects, including dollar limits, service limits, and cost sharing. Minimum mandated benefit (MMB) laws mandate that minimum level of mental health benefits be covered in the health plan, and mental health benefits need not be at same terms and conditions as physical benefits. Mandated if offered laws come in two forms: (i) require private health insurers offer mental healthcare benefits at parity with physical healthcare benefits; however, the decision to purchase the mental healthcare is left to the insured or (ii) require that the insurer offers an insurance with mental healthcare benefits. In general, the strongest type of law is a state-level full parity mental illness law (Lang, 2013; U.S. General Accountability Office, 2000). I examine the effects of state-level full parity mental illness laws for both mental illness and educational outcomes. I choose to study the effect of full parity laws for these outcomes as these laws are likely to have the most impact on use of mental illness treatment and most of current policy discussions in the U.S. at both the federal and state level examine full parity laws (Saloner and Lê Cook, 2014; Antwi et al., 2015; Li and Ye, 2017).

Insurance coverage for mental illness treatments is an important factor that influences individuals' decisions to visit mental healthcare professionals for needed treatment. Indeed, standard economic models of the demand for health and healthcare

[5] I note that while the state-level mental illness parity laws may have stronger regulations, these laws have less scope than the federal laws due to the Employment Retirement Security Act. I return to this issue later in the manuscript.

services suggest that insurance – by reducing the out-of-pocket costs of healthcare services – increases the quantity of healthcare demanded (Grossman, 1972). Therefore, all else equal, state-level full parity mental illness laws should improve access to mental healthcare and, ultimately, reduce mental illness. In addition to state-level full parity mental illness laws increasing utilization of mental healthcare services through the reduction of out-of-pocket prices of these services, these laws may increase access to such services since it is easier for someone to get to see a doctor if they have better quality insurance. Further, if there is any public discourse associated with the implementation of the parity law, there could be increases in the demand for mental illness treatment (e.g., an individual may now think that these treatments are more valuable to them). However, three main factors could limit the coverage of state health insurance regulations and could lessen the predicted impact of state-level full parity mental illness laws. First, self-insured firms are exempt from state mandates, and many state parity laws include explicit exemptions for small firms (typically defined as those with fifty or fewer employees) (Buchmueller et al., 2007). Self-insured firms are exempt from state-level insurance laws under the Employee Retirement Security Act (ERISA) of 1974 (United States Congress, 1974), and employees of large firms are likely to self-insure. Self-insured plans represent more than one-third of workers with employment-based insurance. Thus, ERISA significantly reduces the proportion of a state's population affected by the state mental illness parity laws (Butler, 2000; Busch and Barry, 2008; Klick and Markowitz, 2006; Buchmueller et al., 2007). Buchmueller et al. (2007) find that state-level private health insurance laws only impact approximately half of private sector employees because of exemptions for self-insured plans and small firms.

Second, in response to mental illness parity laws, insurers could implement measures to limit the use of mental healthcare services. Barry and Ridgely (2008) find evidence that health insurers increase their use of supply-side constraints (i.e., mental health carve-outs, utilization reviews, and more restrictive networks) in response to the increased likelihood of moral hazard due to state parity laws.

Third, more generous mental healthcare coverage may increase cost of health insurance, which would reduce affordability of private insurance. Bailey (2014) finds that health insurance benefit mandates increase premiums by 0.44 to 1.11 percent annually. Further, Bailey and Blascak (2016) find that a substantial portion of the cost of mandates is passed on to employees in the form of increased employee contributions to health insurance premiums and thus may reduce private insurance coverage.

2.2 Mental illnesses and mental illness treatment

A mental illness is a condition characterized by a clinically significant disturbance in an individual's cognition, emotion regulation, or behavior that reflects a dysfunction in the psychological, biological, or developmental processes underlying mental functioning (American Psychiatric Association, 2013). Moreover, mental illnesses affect an individual's thinking, feeling, behavior, or mood. These illnesses can make daily activities difficult and impair a person's ability to work, interact with family, and fulfill other major life functions (National Alliance on Mental Illness , 2018b). The development of a mental illness is influenced by genetics, environment, and lifestyle (National Alliance on Mental Illness, 2018). The most recent evidence finds that mental illnesses are most widespread among younger adults than older adults, and most illnesses emerge before individuals reach age 24. In particular, three-quarters of chronic mental illnesses emerge by age 24 (Kessler, Berglund, Demler, Jin, Merikangas and Walters, 2005; Center for Behavioral Health Statistics and Quality, 2016). The reduction of mental illnesses among young adults is crucial because the onset of mental illness early in life can result in a trajectory of adverse academic, occupational, health, and social outcomes. Moreover, it is also important to identify, treat, or prevent mental illnesses among college students, as over 40 percent of American young adults attend a post-secondary institution (McFarland et al., 2018).

There are many different mental illnesses, including depression, bipolar disorder, schizophrenia and other psychoses, dementia, intellectual disabilities, and developmental disorders such as autism (American Psychiatric Association, 2013; National Alliance on Mental Illness, 2018; World Health Organization, 2018a). In particular, college students who suffer from mental illnesses mainly report that they have depression, bipolar disorder, and anxiety (Gruttadaro and Crudo, 2012). The average depression prevalence among college students is 30.6 percent (Ibrahim et al., 2013).[6] In fall 2017, 21.6 percent (17.8 percent) of college students were diagnosed or treated by a professional for anxiety (depression) (American College Health Association, 2018a,b).

Each individual with mental illness will have different experiences, even those with the same diagnosis, and each illness has its own symptoms. However, common signs of mental illness include: confused thinking or difficulty concentrating and learning, changes in school performance, extreme mood changes, excessive sadness, multiple physical ailments without obvious causes, difficulties perceiving reality, changes in sleeping habits, and low energy (National Alliance on Mental Illness, 2018).

In many cases mental illnesses can be successfully managed, allowing individuals to experience relief from their symptoms and have more productive lives, through appropriate treatment. The recovery process of mental illness begins with diagnosis (National Alliance on Mental Illness , 2018a). Mental healthcare providers assess and diagnose mental illnesses. Mental healthcare providers include psychiatrists, psychologists, counselors, clinicians, therapists, clinical social workers, psychiatric or mental health nurse practitioners, and primary care physicians. Mental health professionals work in outpatient facilities, such as community mental health clinics, schools and private practices, and inpatient facilities, such as general hospitals and psychiatric facilities (National Alliance on Mental Illness , 2017). After receiving a diagnosis of a mental illness, most individuals can successfully manage their symptoms with individualized treatment plans. Treatment influences the brain chemicals that regulate emotions and thought patterns and, in turn, improves mental health (National Alliance on Mental Illness, 2018). While it is beyond the scope of this paper to review the full range of treatment options, I next discuss several common options. I refer readers to treatment protocols provided by American Psychiatric Association (2006), National Alliance on Mental Illness (2018b), and Substance Abuse and Mental Health

[6] I refer readers to an excellent review of studies that explore the prevalence of depression in university students by Ibrahim et al. (2013).

Health Services Administration (2017).

Treatment for mental illnesses includes a combination of medication and psychosocial treatments. Psychosocial treatments provide support, education, and guidance to individuals with mental illnesses and their families. These treatments include various types of psychotherapy (such as cognitive behavior therapy, dialectical behavior therapy, interpersonal therapy, and therapy pets), and social and vocational training. However, a psychiatrist may suggest electro-convulsive therapy or other forms of brain stimulation when medication and therapy are not able to relieve the symptoms of serious mental illnesses, such as bipolar disorder and depression with psychosis. Individuals with mental illness emergencies can receive treatment in outpatient and inpatient facilities. An intensive form of treatment is hospitalization at a private psychiatric hospital, general hospital with a psychiatric floor, or state psychiatric hospital. Treatment for mental illness during hospitalization involves observation, diagnosis, changing or adjusting medications, electro-convulsive therapy or other forms of brain stimulation, stabilization, and correcting a harmful living situation. During hospitalization, which includes 24 hours per day treatment, patients receive treatment from psychiatrists, psychiatric nurses, and group therapists.

The effectiveness of mental illness treatment, both medication and psychosocial treatments, in reducing or eliminating symptoms of mental illnesses is well documented. I next briefly discuss effective treatment options for two of the most widespread mental illnesses among college students: depression and anxiety. Numerous studies find that medication-assisted treatment, psychosocial treatment, or combined medicated-assisted and psychosocial treatments for depression reduce depressive symptoms among individuals diagnosed with depression (Calabrese et al., 2005; DeRubeis et al., 2005; Mynors-Wallis et al., 2000; Christensen et al., 2004; Kessler et al., 2009; DeRubeis et al., 2005). The efficacy of psychosocial treatment or combined medicated-assisted and psychosocial treatments for improving mental health among individuals with anxiety is established (Roemer et al., 2008; Hofmann and Smits, 2008; Vøllestad et al., 2011; Blanco et al., 2010).

2.3 Conceptual framework

I next review the theoretical models that motive my analysis of the impact of state-level full parity mental illness laws on mental health among the college-aged population and human capital accumulation in college.

Standard economic models of the demand for health and healthcare services state that the demand for healthcare services is a derived demand (Grossman, 1972). When consumers purchase healthcare services in this model, they do not demand these services *per se*, but rather demand “good health” by utilizing such services. Consumers maximize a utility function of health and other commodities given the price of healthcare services, prices of other commodities, health endowment, health production function, a set of household production functions, a budget constraint, preferences, and other factors that influence health. The demand for healthcare services is downward sloping: the quantity of healthcare services demanded is negatively correlated with its price. By reducing the out-of-pocket costs of healthcare services, healthcare insurance should increase the quantity of healthcare services demanded. Therefore, all else equal, state-level full parity mental illness laws – by reducing the out-of-pocket costs of mental healthcare services – should increase utilization of these services and, ultimately, reduce mental illnesses.

Given that I examine secondary outcomes, it is important to consider the causal pathway from changes in state-level full parity mental illness laws to changes in educational performance in college. I next develop a simple conceptual framework that offers insight into these pathways.

In terms of college grade point average, mental illness may adversely affect an individual’s cognitive achievement, e.g. test scores and GPA, by adversely affecting their ability. In a model that formulates the production function of cognitive achievement, Todd and Wolpin (2003) propose that individual ‘i” achievement level at age ‘a’ is a function of the entire history of family-supplied inputs until age ‘a’, $F_i(a)$, history of school-supplied inputs up to age ‘a’, $S_i(a)$, and genetic endowment of mental capacity to produce a cognitive outcome (abilities), A_{i0}.

$$GPA_{ia} = GPA_a[F_i(a), S_i(a), A_{i0}] \tag{i}$$

In a model of skill formation, Cunha and Heckman (2010) complement the Todd and Wolpin (2003) model by proposing that abilities evolve overtime and are multiple in nature. In their model, students with greater abilities, both cognitive and non–cognitive abilities, are more efficient in learning and gain higher scores on achievement tests. Non-cognitive abilities include patience, self-esteem, self-control, temperament, time preference, and motivation. Given that mental illnesses negatively affect the feelings, thoughts, or moods of individuals, mental illnesses — by adversely affecting college students' non–cognitive abilities – could reduce a student's grade point averages.

Mental illness could also influence a student's decision to drop-out of college. Symptoms of mental illness may decrease concentration and thus may, ultimately, reduce schooling, and mental illnesses can affect the length of employment or life, which make educational investments less valuable (Fletcher, 2008). Therefore, college students with mental illnesses may invest less in education and decide to leave college before graduating. I briefly summarize Fletcher (2008) model that illustrates the potential mechanisms through which mental illness can influence human capital accumulation in college here.

Fletcher (2008) utilizes a simple model of human capital accumulation (Rosen, 1977) to assume a deterministic relationship between earnings, y, and years of schooling, s:

$$y = f(s; A) \tag{ii}$$

where A is a person-specific variable such as ability or other mental faculties that shift the earnings-schooling function. In this setup, individuals choose years of schooling to maximize their present discounted value of future income:

$$v(s) = \int_R^s y(s; A)\epsilon^{rt} dt \tag{iii}$$

where r is the interest rate and R is the age of (exogenous) retirement or death. In this simple model, a student may maximize their value function by dropping out of college if their mental illness worsens, or a student might have been able to reach an optimum (at a higher level of utility) by remaining in college if their symptoms were reduced or eliminated (Eisenberg et al., 2009). In particular, mental illnesses could reduce the marginal return of continuing college by decreasing an individual's ability or capacity to learn and thus reducing scores on their achievement level tests. The reduction in test scores and GPA may be a poor signal to future employers, which may cause a student with mental illness to drop out of college. Mental illnesses may also affect the length of employment or life, R, which makes educational investments less valuable.

I use the preceding discussion to generate predictions on the extent to which the state-level full parity mental illness laws will affect mental illness among the college-aged population and human capital accumulation in college. I hypothesize that the passage of state-level full parity mental illness laws – by reducing the out-of-pocket costs of mental healthcare services and increasing utilization of mental healthcare services – will reduce mental illness among the college-aged population, increase college students' GPA, and decrease the propensity to drop out of college.

2.4 Related literature

This study builds on three literatures: those that studied the effect of mental illnesses on human capital accumulation, those that analyzed the impact of state-level mental illness parity laws on various outcomes, and those that examined the effect of policies that increased generosity for private insurance coverage of mental healthcare treatments on utilization of these treatments. I first consider the studies that examine the impact of mental illnesses on human capital accumulation. Mental illnesses may negatively impact human accumulation by reducing both the amount of schooling and its productivity (Cornaglia et al., 2015). Breslau et al. (2011) find that mental illnesses are significantly associated with termination of schooling prior to completion of each of the four educational milestones (elementary school graduation, high school graduation, college entry, and college graduation). In addition, mental illnesses are negatively correlated with GPAs of college students (Eisenberg et al., 2009). Given that mental illness treatments are effective in improving mental health and mental illnesses adversely affect college GPA, college students with mental illnesses could improve their GPAs if they utilize mental illness treatments.

State-level full parity mental illness laws could improve human capital accumulation in college for students with mental illness, because these laws were implemented to reduce the out-of-pocket costs of mental healthcare services, increase utilization of these services and, ultimately, reduce mental illness. Indeed studies find that state mental illness parity laws have been effective with increasing utilization of mental health services and reducing the financial burden on families of children with mental healthcare needs (Busch and Barry, 2007, 2008). Further, state-level mental illness parity laws improve mental health and productivity. Lang (2013) finds that these parity laws significantly reduce the state-level suicide rate, and Andersen (2015) concludes that the mandates increase working hours and wages among employees with mental illnesses.

Studies that examine the effects of other laws that regulate private insurance markets and expand coverage for mental illness treatments find that these laws increase the utilization of mental healthcare services and improve mental health. For instance, Saloner and Lê Cook (2014) find that the use of mental illness treatment among young adults increased by 5.3 percentage points relative to a comparison group of older adults following the implementation of the ACA provision. Further, Antwi et al. (2015) find that young adults increased their mental-illness-related inpatient visits by 9 percent relative to older adults following the implementation of the ACA provision.

3 Data and key variables

3.1 State mental illness parity laws

I include data on state-level mental illness parity laws, based on Lang (2013), to indicate whether a state had a mental illness parity law implemented in a given year and to classify the parity laws.[7] Table 1 reports the date (month and year) of implementation of the state mental illness parity law for states that passed a full parity or minimum mandated law by 2008. Twenty-four states passed a full parity mental illness law between 1998 and 2008, and 9 states passed a minimum mandated benefit law. I match the implementation dates to the administrative and survey datasets by state and year.

3.2 Outcome variables

To examine the effect of state-level full parity mental illness laws on the suicide rate among the college-aged population (20-34 years old), I draw data from the public use Compressed Mortality File (CMF) of Centers for Disease Control and Prevention (CDC) from 1998 to 2008. I use this age range because this is the best suited age range in the data that overlaps with the age range in the educational outcomes models. Specifically, I use the mortality data in the CMF. These data are based on information from all death certificates filed in the fifty states and the District of Columbia. Only the deaths of U.S. residents who lived in the U.S. at the time of their death are included. The underlying cause of death is the classified injury intent and mechanism. The CDC suppresses state-level age-group specific data for zero to nine deaths. For the analysis, I use values of 0 to impute the missing data that results from the suppression.[8]

Given that suicide is an extreme measure of mental illness, I use an indicator for whether an individual reported any poor mental health day in the last 30 days as another measure of mental health. Number of poor mental health days is a self-assessed measure and not a clinical measure. Self-assessed measures of mental illness are often the quickest and easiest way to determine how individuals feel about their mental health. For this mental health outcome, I draw data from the state-based Behavioral Risk Factor Surveillance System (BRFSS) from 1998 to 2008. BRFSS

[7] I thank Matthew Lang for sharing the updated data on parity laws and years of passage.

[8] I imputed 4 of the 561 observations. As a robustness check, I use values of 5 and 9 to impute the missing data. The results are not appreciably different from using 0 to impute the missing data. Results are reported in Appendix Table A1.

was established by the CDC, and collects data from adult U.S. residents regarding their health-related risk behaviors, chronic health conditions, and use of preventive services. For my analysis, I use an indicator for whether an individual reported any poor mental health day in the last 30 days for the respondents from 20 to 34 years old. This age range is used to match the age range in the models with suicide as an outcome.

To examine the effects of state-level full parity mental illness laws on educational outcomes in college, I use data from the publicly available National Longitudinal Survey of Youth 1997 Cohort (NLSY97) that is administered by the U.S. Bureau of Labor Statistics and conducted by the National Opinion Research Center at the University of Chicago, with assistance from the Center for Human Resource Research at The Ohio State University. Specifically, I also use the NLSY97 geocoded data, which allows me to determine the state of residence for each respondent. The NLSY97 Cohort is a nationally representative sample of American youths born between 1980 and 1984. The NLSY97 data are based on surveys that started in 1997 with 8,984 youths who were 12-17 years old. These individuals have been interviewed 16 times to date. Data are now available from Round 1 (1997-98) to Round 16 (2013-14). These data are well suited for my study because the NLSY97 contains information on college experiences and educational outcomes, as well as demographic data. Specifically, the NLSY97 contains post-secondary transcript information for each term, and self-reported college experience information for each month and term. One of the key advantages of using the NLSY97 transcript data is that it allows me to assess accurate educational history for each college student and remove concerns of self-reported errors. In addition, the NLSY97 is ideal to study the passage of the state-level full parity mental illness laws because most of these laws were passed in the late 1990s and early 2000s and most of the NLSY97 cohort graduated from high school, and made their college choice, during this time period.

I focus on two standard educational outcome variables using the college experience data of the NLSY97. As a measure of the student's academic performance while enrolled in college, I use the transcript GPA to calculate the average GPA across all terms in the calendar year. Transcript GPA is measured on a four-point scale. In addition, using the monthly school enrollment information from the NLSY97, as an outcome, I focus on the student's decision to drop out of college before graduating.[9]

There is no information on mental illness treatment for my study period in the CMF, BRFSS, or NLSY97. Thus, I cannot estimate the 'first stage' regression, the effect of state-level full parity mental illness laws on mental illness treatment, and use this estimate to 'scale up' the effect of these laws on mental illness and educational outcomes. Thus, my estimates have an intent-to-treat (ITT) interpretation, and illustrate the secondary pathways through which state-level full parity mental illness laws affect educational performance in college and mental illness among the college-aged population.

3.3 Controls

To address omitted variable bias, I include measures of state-level characteristics to control for state time-varying factors that are likely to be correlated with the passage of the state-level full parity mental illness laws, and the educational and mental health outcomes. I use data from the University of Kentucky Center for Poverty Research (2016) on the unemployment rate, state minimum wage, maximum monthly Temporary Assistance for Needy Families (TANF) benefits for a family of four, and whether the governor is a Democrat. To determine the percentage of employees in large firms with over 500 employees, I use data from U.S. Small Business Administration (2014). Large firms in the U.S. are more likely to self-insure, and self-insured firms are exempt from state-level mandates under the ERISA (United States Congress, 1974). From the Annual Social and Economic Supplement of the Current Population Survey (ASEC-CPS), I use state-level percentage of males, percentage of single and separated, divorced, or widowed population, percentage of less than high school, high school, and college educated population. To determine the passage of health insurance parity laws for substance use disorder treatment, I use data from Popovici

[9] I use the transcript data to fill missing monthly enrollment data. Students drop out of college if they leave their college before graduating. Transfer students who are enrolled in college for every month of the year are not coded as dropouts. 5.756 percent observations were filled.

et al. (2017). I use data from Hamersma and Kim (2013) to determine the state-level Medicaid income eligibility threshold.[10] I merge state-level control variables with the state-level mortality data from CMF for the suicide rate outcome models. For the propensity to report any poor mental health day in the last 30 days models, I merge state-level variables with the state of residence of each respondent into the BRFSS. Likewise, I merge state-level variables with the state of residence of each respondent into the NLSY97 for the educational outcomes models.

For the models with educational outcomes, I include a set of pre-determined individual level variables from the NLSY97 that are likely to affect the educational performance of the respondent: biological parents' educational attainment (mother's and father's highest year of education entered linearly and separated), race/ethnicity (Non-Black/Non-Hispanic, African American, and Hispanic, with Mixed Race as the reference group), household size, household income relative to the federal poverty level ratio (FPL) in 1996 (100 to 199 percent of FPL, 200 to 299 percent of FPL, 300 to 399 percent of FPL, and over 400 percent of FPL, with below 100 percent of poverty as the reference group),[11] family structure at age 12 (lived with single mother, lived with a step parent, and other family structure,[12] lived with both biological parents as the reference group), age, urban residence, marital status (married and separated, single, or widowed, with never married as the reference group), urban residence status, and a proxy for ability (the composite math and verbal aptitude percentile score from the ASVAB - Armed Services Vocational Aptitude Battery- tests).

For the missing FPL ratio in 1996, I assign the average federal poverty level within the household for the sample period. For other missing observations, I assign the sample mean for the continuous variables; and the sample mode for the categorical variables.[13] All regressions are estimated with indicator variables for missing

[10] I thank Sarah Hamersma for sharing the updated Medicaid income eligibility threshold data.

[11] Information on the household's income in 1996 and parents' educational achievement were collected from the 1997 survey.

[12] Other family structure is defined as those that lived with adoptive parent(s), foster parent(s), biological dad (with marital status unknown), group quarters, or other adults (with biological parent status unknown, not group quarters).

[13] I estimate the models without imputing values for the missing data. That is, I apply listwise deletion to the data. The magnitude of the coefficients decrease and the p-values increase from the models with the imputed values for missing data. I suspect that the precision of the estimates

information.

3.4 Empirical model

I use a differences-in-differences (DD) model to empirically test the effect of passing state-level full parity mental illness laws on educational and mental illness outcomes. The primary analysis exploits variation across states and time in the implementation of mental illness parity laws to identify the effects of the laws on college students' academic success and the mental health of the college-aged population. The identifying variation for the primary analysis comes from the within-state law changes. The basic specification used to isolate this effect is:

$$Y_{ist} = \beta_0 + MHPL'_{st}\beta_1 + X_{ist}\beta_2 + C_{st}\beta_3 + \tau_t + \gamma_s + \epsilon_{ist} \tag{1}$$

where Y_{ist} is an outcome for individual i in state s during year t. The variable of interest is $MHPL_{st}$. $MHPL_{st}$ is equal to the fraction of the year for which the state-level full parity mental illness law was passed. This variable is coded as zero for years before the implementation of the law and one for years after the implementation of the law. For example, if a law became effective on January 1st, 2005, I code $MHPL_{st}$ as 1 in 2005, and if a law became effective on July 1st, 2006, I code $MHPL_{st}$ as 0.5 in 2006. X_{ist} is a vector of individual covariates - race/ethnicity, gender, age, marital status, household poverty status, and parents' educational attainment. C_{st} is a vector of state-level covariates. α_s and τ_t are vectors of state and year fixed effects, respectively. Inclusion of the state fixed effects controls for time-invariant factors that impact the educational (or mental health) outcomes within a state. The year fixed effects control for national secular trends in college educational outcomes (or mental health). ϵ_{ist} is the error term.[14]

I use OLS for the continuous outcomes and linear probability models for the binary outcomes. Standard errors are clustered at the state-level. I use 51 clusters to consistently estimate the standard errors (Cameron and Miller, 2015).

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decline because of the small sample size. Results are reported in Appendix Table A2.

[14]Unit of observation is the state-year for the model with suicide as an outcome. Thus, Y is an outcome for state s in year t, and this model does not include individual level controls.

4 Results

4.1 Summary statistics

Table 2 reports unweighted descriptive statistics for the analysis sample of the educational outcomes. The means indicate that the students are predominantly Non-Hispanic and Non-Black (60.8 percent), and single (91.5 percent). The sample has a slightly lower percentage of males (43.9 percent). The average GPA score is 2.596. Twenty percent of the sample reported not attending college for at least one semester before graduating or dropping out completely out of college before graduating. Parents completed an average of 13.5 years of schooling, and majority (62.7 percent) of the sample lived with both of their biological parents at age 12. In addition, 9.6 percent reported a household income below the poverty line in 1996.

4.2 Regression analysis

To establish the causal pathway of the effect of state-level full parity mental illness laws on human capital accumulation in college, I examine the effect of these laws on mental illness outcomes, and then I study the impact of these laws on educational outcomes in college.

4.2.1 Regression analysis of mental health outcomes

To determine the effect of state-level mental illness full parity laws on mental illness, I first examine the effect of these laws on the log of the suicide rate per 100,000. The findings are reported in Table 3. I find that passage of a full parity mental illness law leads to a significant decrease in suicide rate by 3.5 percent for the college-aged population. These results suggest that state-level full parity mental illness laws are effective at reducing suicide among the college-aged population.

Given that suicide represents an extreme and often acute manifestation of mental illnesses (Tannenbaum et al., 2009). I next examine the effect of full parity mental illness laws on the propensity to report any poor mental health day in the last 30 days. Table 4 reports the results. I find that the passage of a full mental illness parity law reduces the probability to report any poor mental health day by 1.8 percentage points among the college aged-population. The coefficient estimate is statistically significant at the 1 percent level. These results suggest that state-level full parity mental illness laws are effective in reducing the self-reported mental illness.

4.2.2 Regression analysis of educational outcomes

Table 5 reports the results of the effect of full mental illness parity law (MHPL) on the educational outcomes. I find that average annual GPA increases by 0.110 post-MHPL, which is equivalent to 4.24 percent of the sample mean. The coefficient estimate is statistically significantly different from zero at the 5 percent level. The finding of small changes of the GPA is in line with the education literature, as several authors who examine factors which affect GPA find that GPA changes are small (Griffith and Rask, 2014; Eisenberg et al., 2009; Kuh, 2008). Small changes in GPA would be due to the strong concentration of GPA measure.[15] Further, I find no statistically significant evidence that the MHPLs affect the propensity to drop out of college. Thus, the state-level full parity mental illness laws are not likely to affect the composition of students and, in turn, the analyses of GPA variables are not vulnerable to conditional-on-positive bias (Angrist and Pischke, 2009).

4.3 Internal validity

A potential threat to my identification strategy is that states passed full parity mental illness laws with the intent to influence the educational outcomes of the college students (or mental illness outcomes of the college-aged population), or the educational outcomes (the mental illness outcomes) could influence the passage of the state mental illness law. If true, the estimated β_1 in Equation 1 would be biased due to reverse causality. In order to test for policy endogeneity in passage of state mental illness parity laws, I examine the pattern of lead and lag effects of the policy by estimating an event study (Autor, 2003; Stevenson and Wolfers, 2006; Angrist and Pischke, 2009). I re-estimate Equation 1 by including a series of dummies coding the year of policy passage and one to three years both pre- and post-policy implementation ($MHPL^k_{st}$,

[15] GPA has a strong concentration because it is measured from a 0.0 to 4.0 scale.

-3 $\leqslant k \leqslant$ 3). Equation 2 outlines the specification of my event study analysis.

$$Y_{ist} = \theta_0 + \sum_{k=-3}^{3} \sigma_k MHPL_{st}^k + X_{ist}\theta_1 + C_{st}\theta_2 + \tau_t + \gamma_s + \epsilon_{ist} \tag{2}$$

I set all pre- and post-policy implementation dummies to zero for the states that never passed the state mental illness full parity law (Lovenheim, 2009). Following Kline (2011), I impose 'end point' restrictions: I assume there are no anticipatory effects more than three years in advance of the passage of state-level full parity mental illness laws and the parity law effects fade out after three years post-law. Policy endogeneity is not a concern if the coefficients of the policy leads are statistically insignificant from zero. The use of policy lags allows me to examine the policy-dynamics.

Results for the event studies for the mental illness outcomes are reported graphically in Figures 1 and 2. I report the coefficient estimates and associated 95 percent confidence intervals that account for within-state clustering for each lead or lag. The event studies show that all of the estimated coefficients for the leads are not statistically distinguishable from zero. These findings provide suggestive evidence of the absence of policy endogeneity. The event study results for the suicide rate outcome in Figure 1 show that the parity law only significantly impacts suicide in the year that the law is passed. However, Figure 2 shows that the propensity to report any poor mental health day decreases in the post-treatment years.

Table 6, Figure 3, and Figure 4 report the event studies results for the educational outcomes. The estimates of the coefficients of the leads are not statistically different from zero. Thus, I do not observe any evidence of policy endogeneity for the educational outcomes. I find no statistically significant evidence that the MHPLs change the decision to drop out of college for students in the post-treatment periods. After the passage of the full parity mental illness law, I observe that there is an immediate increase in annual average GPA by 0.132 points, and GPA gradually increases in the post-law years.

5 Robustness checks and extensions

I next report results from robustness checks to examine the stability of my findings for the educational outcomes.

5.1 Differential control for between state heterogeneity

5.1.1 State-specific linear time trends

I estimated augmented versions of Equation 1 that include state-specific linear time trends. Specifically, I multiplied each state fixed effect by a linear time trend. In other words, I estimated:

$$Y_{ist} = \eta_0 + MHPL'_{st}\eta_1 + X_{ist}\eta_2 + C_{st}\eta_3 + \tau_t + \gamma_s + \Omega_{st} + \epsilon_{ist} \tag{3}$$

where Ω_{st} is a vector of state-specific linear time trends. State-specific linear time trends were included to control for unobserved state-level time-varying characteristics and allow each state to follow a different linear trend in outcomes. These results are reported in Table 7. The inclusion of the state-specific linear time trends leads to reduction in the magnitude of the estimated effects of the passage of state-level full parity mental illness law on GPA and reduction of the precision of the estimates. The change in precision is perhaps not surprising as models with state-specific linear time trends are saturated and data hungry. Further, I find no statistically significant evidence that the passage of a full parity mental illness law affects the propensity to drop out of college.

5.1.2 Factor model

The identification assumption in my main specification, Equation 1, is that educational outcomes are uncorrelated with the error term ϵ_{ist} conditional on the state fixed effects, year fixed effects, and other controls. However, this specification does not allow for the presence of cross section dependence remaining in the error term. In this study, cross section dependence could arise if the residuals are correlated across states, i.e. if there are unobserved common factors (such as economic, political, social, and cultural ties) between states. Cross section dependence could cause my estimates to be biased if the unobserved common factors between states are correlated with the regressors (Totty, 2017; Bai, 2009). The factor model approach controls for cross section dependence through time-specific common factors that can have heterogeneous effects over states:[16]

$$\epsilon_{ist} = \lambda_{is} f_t + \mu_{ist} \tag{4}$$

where λ_{is} is an r-dimensional factor loading representing the heterogeneous response of y_{ist} to the common factor f_t. In this setup, variation in the educational outcomes is uncorrelated with the error term μ_{ist} conditional on the state fixed effects, year fixed effects, other controls, common factors, and factor loadings.

For an additional robustness check, I utilize the factor model to account for unobserved heterogeneity. In theory, the factor model could be approximated by adding linear, quadratic, and cubic state-specific time trends to the baseline differences-in-differences model, Equation 1, but that comes with the cost of efficiency and statistical power. The factor model uses less degrees of freedom while controlling for flexible time trends. Factor models are estimated based on the main specification in Equation 1 and the multi-factor error structure in Equation 4. To estimate the multi-factor error structure, I use the interactive fixed effects approach from Bai (2009). The interactive fixed effects will not produce similar results to Equation 1 if there are state-specific time trends unaccounted for in the main specification. Table 8 reports the interactive fixed effects results and demonstrates robustness of my DD results.

5.1.3 Alternative regression specifications

Table 9 demonstrates robustness of my results to alternative regression specification. In my main specification, I control for between-state heterogeneity by including time-varying state characteristics (e.g., unemployment rate) and state fixed effects. While this is a standard specification within the state-level mental illness parity laws literature (Lang, 2013; Andersen, 2015), a concern with this specification is that some of the time-varying state-level controls may in fact be outcomes of the MHPLs and including these variables in the regression may lead to over-controlling bias. Fur-

[16] I refer readers to Totty (2017) for an excellent review of the application of factor models.

ther, in the main specification, individual-level controls are not likely to be a source of omitted variable bias, but these controls are included to increase precision (Angrist and Pischke, 2009). Thus, I estimated regressions that exclude the time-varying state-level variables and individual-level controls. While I lose some precision, the p-value of the GPA effects is 0.064. Further, the magnitude of the estimated effect of the passage of state-level full parity mental illness laws on GPA increased slightly.

5.2 Heterogeneity in MHPL effects by sex

There are established sex differences in terms of mental illness and mental illness treatment (e.g., males are less likely to experience mental illnesses and males with mental illnesses are less likely to receive treatment than females (Substance Abuse and Mental Health Services Administration, 2015; Gruttadaro and Crudo, 2012)). In addition, there are established sex differences in college performance and persistence (e.g., male students earn lower grades in college than females and male students are less likely to persist and graduate from college (Conger and Long, 2010)). To explore such heterogeneity, I estimated separate regressions for males and females. Appendix Table A3 reports results on the effects of MHPL passage on educational outcomes for females. Appendix Table A4 reports results on the effects of MHPL passage on educational outcomes for males. I find heterogeneity in education effects across gender. Females, not males, improve educational performance post-MHPL. More specifically, passage of a full parity law leads to a 0.168 increase in GPA for female students, which is equivalent to 6.35 percent of the sample mean. However, I find no statistically significant evidence that passage of a full parity law affects GPA among male students. Additionally, I find no statistically significant evidence that passage of a full parity law leads to changes in the propensity to drop out of college among both genders.

5.3 Placebo tests

I perform an analysis with placebo laws to further test the validity of my DD design. Using the data prior to the passage of the full parity law for the treatment group and excluding states that passed the law before 2001,[17] I randomly assign a 'false' MHPL passage year to states. I next construct an indicator coded one if a state has a 'false' MHPL and zero otherwise. I re-estimate a variant of my core regression models (Equation 1) for the educational outcomes by replacing the mental illness parity law with the placebo law. Results are reported in Appendix Table A5. I find no statistically significant evidence that the educational performance of college students changed following the passage of the placebo laws: all of the coefficient estimates on the placebo laws are statistically indistinguishable from zero. These regressions provide further support to the validity of my DD design.

5.4 Additional robustness checks and extensions

5.4.1 Weighting

All of the estimated regressions for the educational outcomes presented thus far are unweighted. There is controversy within the economics literature regarding whether weighting data is appropriate when estimating the causal effects of a given treatment (Angrist and Pischke, 2009; Solon et al., 2015). Given this controversy, I re-estimate Equation 1 using NLSY97 survey weights. Results are reported in Appendix Table A6 and are not appreciably different from the unweighted results.

5.4.2 Migration

A concern in policy analyses is program-induced interstate migration (Moffitt, 1992). My coefficient estimates could be biased if college students moved to MHPL states as a result of law passage. To test this possibility, I regress an indicator of whether a college student moved across state between previous and current survey years on the MHPL status of the state of residence from the previous survey year and other controls in the baseline model (Equation 1). Appendix Table A7 provides estimates of the impact of full parity laws on the propensity to migrate across state. I find no statistically significant evidence that the migration of college students across state lines is influenced by MHPLs.

[17] I exclude the states that passed the law early in order to have at least three years of data for a given state.

5.4.3 Scope of laws

While majority of the states that implemented full parity mental illness laws during my study period implemented a parity law for the first time, some states transitioned from minimum mandated benefits laws. Thus, the treatment 'dose' may vary across sates; e.g., the dose may be larger for full parity states that had no existing laws than for full parity states than transitioned from minimum mandated benefits. To explore such possibility, I estimated a variant of Equation 1 by including an indicator for state-level minimum mandated benefits laws (MMB). This indicator variable is coded one if a state has an MMB in place in time 't' and zero if a state has no MMB or a full parity law in time 't'. Results are reported in Appendix Table A8. The coefficient estimate from the GPA model is slightly smaller than the baseline estimate. The findings suggest that the treatment 'dose' of the full parity laws is smaller for states that transitioned from minimum mandated benefit laws.

5.4.4 Alternative samples: Excluding small state cells

Some of the state cells are small, because the NLSY97 is representative at the national, not state, level. I test the sensitivity of my main DD results by excluding students whose state of residence is too small (less than 20 students). Results are reported in Appendix Table 9 and are not appreciably different from my core findings.

6 Discussion

Prior research finds that there is a high prevalence of mental health problems in college students. In the late 1990s and 2000s, state-level mental illness parity laws were passed to increase the utilization of mental illness treatments. Studies find that the state mental illness laws are effective at increasing use of mental health services and improving labor market outcomes. I add to the literature of the effect of the state mental illness parity laws by examining the impact of these laws on educational outcomes of young adults. Specifically, this is the first study to explore the effects of state-level full parity mental illness laws on educational outcomes for college students: grade point average and propensity to drop out of college. Using differences-in-differences estimation design to estimate the effect of state-level mental illness parity laws on educational outcomes, I find that the passage of a full parity law leads to a small increase in the GPA of college students. However, I find no evidence that state-level full parity mental illness law changes the college dropout rate. Thus, the parity laws do not likely affect the composition of students and, in turn, the analyses of GPA variables are not vulnerable to conditional-on-positive bias.

I can use my estimates of the GPA effects to predict the effect of full parity for states that did not pass a full parity law by 2008 (Maclean et al., 2018). For example, taking my estimate at face value I predict that the passage of a full parity law in all states that did not pass such law by 2008 would increase college students' GPA by an average of 0.106 GPA points.[18]

I also find that the passage of a state-level full parity mental illness law reduces the state-level suicide rate and propensity to report any poor mental health day in the past 30 days among the college-aged population. However, it is important to note that state mental illness parity laws could affect both the extensive and intensive margins of mental illness treatment. To examine the effect of these laws on the extensive margin, I estimate the effect of state-level full parity mental illness laws on insurance coverage among the college-aged population. I find that the passage of a full parity law does not change the propensity for an individual to have private insurance coverage. Further, I find no statistically significant effect of state-level full parity mental illness laws on public insurance coverage, which provides further suggestive evidence that these laws do not result in individuals transitioning from public insurance to private insurance to take up coverage that offers more generous mental healthcare benefits.[19] The effect of the state-level full parity mental illness laws could work through the intensive margin by increasing the generosity of mental healthcare coverage for privately insured individuals who had mental healthcare coverage in the pre-law period or allowing privately insured individuals to gain mental healthcare coverage.

[18]Average per state is calculated by applying the 4.2 percent to the average GPA of students in states that did not pass a full parity law by 2008.

[19]These results are reported in Appendix Table A10.

My study has some limitations. (i) I cannot examine the relationship between mental illness parity laws and mental healthcare treatment at the intensive margin. (ii) I rely on survey data from the NLYS97 and BRFSS datasets and there might be some reporting errors. In particular, individuals may under report the number of poor mental health days because of the stigma associated with mental illness. (iii) Reports of poor mental health days are self-assessed, and not clinical, measures of mental illnesses. (iv) My identification strategy is necessarily limited to the variation in the mental illness parity laws from states that implemented laws during my study period. (v) I estimate intent-to-treat models instead of treatment-on-treated models. However, an intent-to-treat is a useful tool for policy, because state mental illness parity laws are the lever available to policymakers. Further, my results are comparable to other ITT effects reported in the literature. For instance, Lang (2013) shows a 5 percent decline in suicide rate post state mental illness parity law.

The findings from this study can provide insights into the impact of the Affordable Care Act (ACA), since the federal government took steps to provide coverage that is more comprehensive for mental healthcare services under the ACA. Specifically, it suggests that the ACA will improve the college-level educational outcomes of youths in the U.S. Further, the findings add to the existing literature that suggests mental illness adversely affects human capital accumulation. Specifically, mental illness treatments significantly increase productivity at work (Berndt et al., 1998), improve labor market outcomes (Andersen, 2015), and increase college-level GPA. My findings suggest that full parity mental illness laws are vital to the improvement and maintenance of a skilled workforce for the U.S. economy.

Table 1: **State mental health parity laws as of 2008**

Full Parity States	Passage Date
Alabama	**Jan-01**
Arkansas	Aug-97
California	**Jul-00**
Colorado	**Jan-98**
Connecticut	**Jan-00**
Delaware	**Jan-99**
Hawaii	**Jul-99**
Illinois	**Jan-02**
Iowa	**Jan-06**
Kansas	**Jan-02**
Louisiana	**Jan-01**
Maine	Jan-96
Maryland	Jul-95
Massachusetts	**Jan-02**
Minnesota	Aug-95
Montana	**Jan-00**
New Hampshire	Jan-95
New Jersey	**Jan-00**
New Mexico	**Jan-00**
New York	**Jan99**
North Dakota	Jan-96
Ohio	**Jan-08**
Oklahoma	**Jan-00**
Oregon	**Jan-07**
Rhode Island	Jan-95
South Dakota	**Jul-98**
Texas	**Jan-98**
Utah	**Jan-01**
Vermont	**Jan-98**
Virginia	**Jan-00**
West Virginia	**Jul-02**
MMB- Minimum Mandated Benefits States	
Colorado	Jul-92
District of Columbia	**Jan-99**
Hawaii	Jan-88
Illinois	Jan-91
Kansas	**Jan-98**
Massachusetts	Jan-96
Michigan	**Jul-00**
Mississippi	**Jan-02**

Table 1: (continued)

MMB- Minimum Mandated Benefits States	
Nevada	**Jan-00**
Pennsylvania	**Apr-99**
Tennessee	**Jul-99**
Wisconsin	**Jan-98**

Notes. Data source: Lang (2013). I thank Matthew Lang for providing updated state mental illness parity laws.

Table 2: Summary statistics: NLSY97: 1998-2008 sample

	Mean/proportion	Standard Deviation
Outcome Variables		
Annual Average GPA	2.596	1.126
Dropped out of college, past year	0.198	0.398
Demographics		
Age at the interview date	21.050	2.318
Male	0.439	0.496
White	0.608	0.488
Black	0.197	0.398
Hispanic	0.173	0.374
Mixed race (Non-Hispanic)	0.011	0.105
ASVAB	59.14	24.71
Father's education	13.58	2.882
Mother's education	13.41	2.878
Household size	3.450	1.533
Marital status		
Never married	0.915	0.279
Married	0.075	0.263
Separated, divorced, or widowed	0.010	0.100
Household income relative to the federal poverty ratio (1996)		
<100% of FPL	0.096	0.295
100-199% of FPL	0.163	0.369
200-299% of FPL	0.198	0.398
300-399% of FPL	0.198	0.399
400% plus of FPL	0.345	0.475
Urban Residence	0.811	0.391
Youth lived with both biological parents at age 12		
Yes, lived with both biological parents	0.627	0.484
Step-parent	0.043	0.203
Single mother	0.262	0.440
Other	0.068	0.251
State-level characteristics		
Unemployment rate	5.158	1.104
SUD parity laws	0.071	0.253
Poverty rate	12.350	2.734
State minimum wage ($)	6.584	0.741
Max monthly TANF benefit for a family of 4 ($)	579.2	227.55
Medicaid ($)	1014.10	581.80
Proportion of workers in large firms	0.493	0.039
Democrat governor	0.478	0.500
Male	0.515	0.009
Separated, divorced, or widowed	0.125	0.014
Single	0.461	0.026
Less than high school	0.424	0.038
High school	0.217	0.032
College	0.170	0.030
Observations	12737	12737

Table 3: The effect of state mental health parity laws on mental health outcomes. CDC's Compressed Mortality File (CMF): 1998-2008

Outcome:	Log suicide rate
Sample mean	2.709
Full parity law	-0.035**
	(0.023)
	[-0.065,-0.005]
Observations	561

Notes: All models are estimated with OLS, and controls for demographics, year fixed effects, and state fixed effects. Population weights applied. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***, **,* = statistically different from zero at the 1%, 5%, 10% level.

Table 4: The effect of state mental health parity laws on mental health outcomes: BRFSS 1998-2008

Outcome:	Poor mental health days in the last 30 days
Sample mean	0.425
Full parity law	-0.018***
	(0.001)
	[-0.029,-0.007]
Observations	485687

Notes: Ages 20-34. All models are estimated with linear probability models, and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. P-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***, **,* = statistically different from zero at the 1%, 5%, 10% level.

Table 5: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008

Outcome:	Annual Average GPA	Drop out
Sample mean	2.596	0.198
Full parity	0.110**	0.008
	(0.015)	(0.700)
	[0.022,0.198]	[-0.033,0.049]
N	12737	12737

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Table 6: Effect of state full parity mental illness laws on college educational outcomes using an event study: NLSY97 1998-2008

Outcome:	Annual Average GPA	Drop out
3 years pre-law	0.052	0.001
	(0.397)	(0.985)
2 years pre-law	0.058	-0.005
	(0.383)	(0.871)
Law year	0.132**	-0.001
	(0.034)	(0.962)
1 year post-law	0.132**	0.004
	(0.041)	(0.827)
2 years post-law	0.144**	0.031
	(0.014)	(0.127)
3 years post-law	0.184***	0.031
	(0.004)	(0.224)
Observations	12737	12737

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. ***, **,* = statistically different from zero at the 1%, 5%, 10% level.

Table 7: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of state-specific linear time trends inclusion

Outcome:	Annual Average GPA	Drop out
Sample mean	2.596	0.198
Full parity	0.074	-0.010
	(0.123)	(0.674)
	[-0.021,0.168]	[-0.058,0.038]
N	12737	12737

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects and state fixed effects, and state-specific linear time trends. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Table 8: The effect of full-parity state mental health parity laws on college academic outcomes NLSY97 1998 - 2008: Robustness tests of interactive fixed effects

Outcome:	Annual Average GPA	Drop out
Sample mean	2.596	0.198
One Factor	0.119**	-0.014
	(0.030)	(0.421)
Two factors	0.118**	-0.009
	(0.020)	(0.755)
Three factors	0.148**	0.008
	(0.050)	(0.786)
Four factors	0.124*	-0.086**
	(0.088)	(0.018)
N	12737	12737

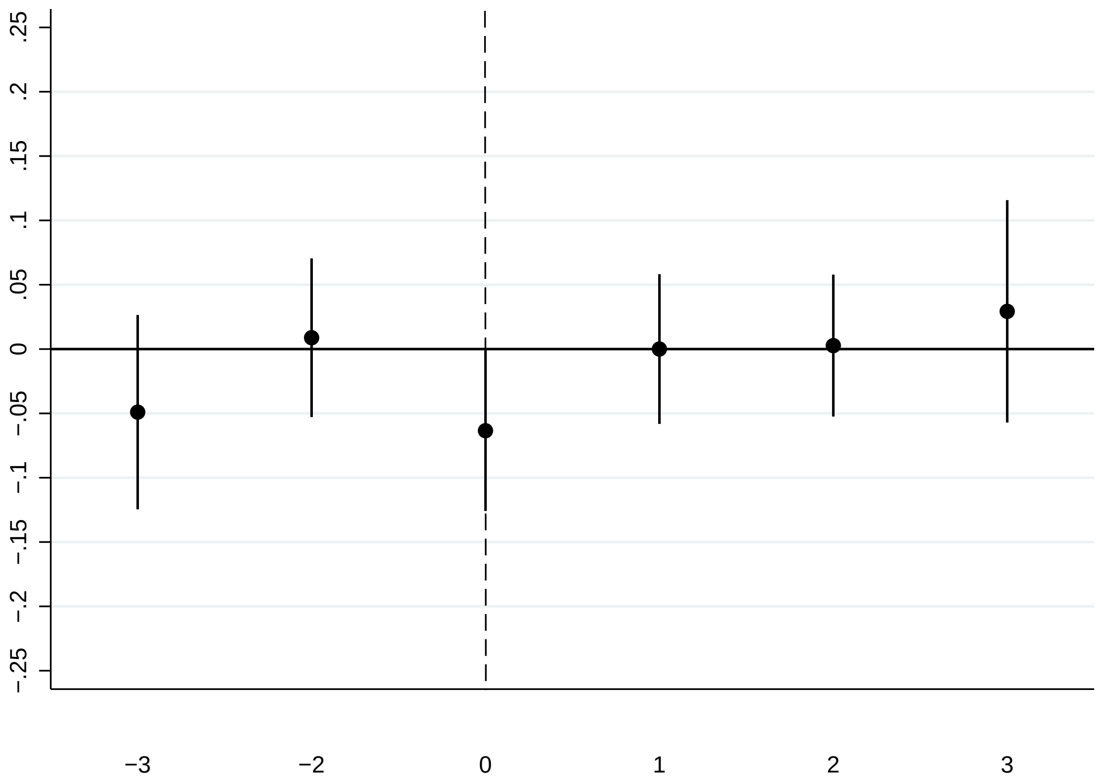
Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects and state fixed effects, and state-specific linear time trends. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Table 9: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of alternative regression specification

Outcome:	Annual Average GPA	Drop out
Sample mean	2.596	0.198
Full parity	0.116*	0.002
	(0.064)	(0.940)
	[-0.007,0.238]	[-0.040,0.044]
N	12737	12737

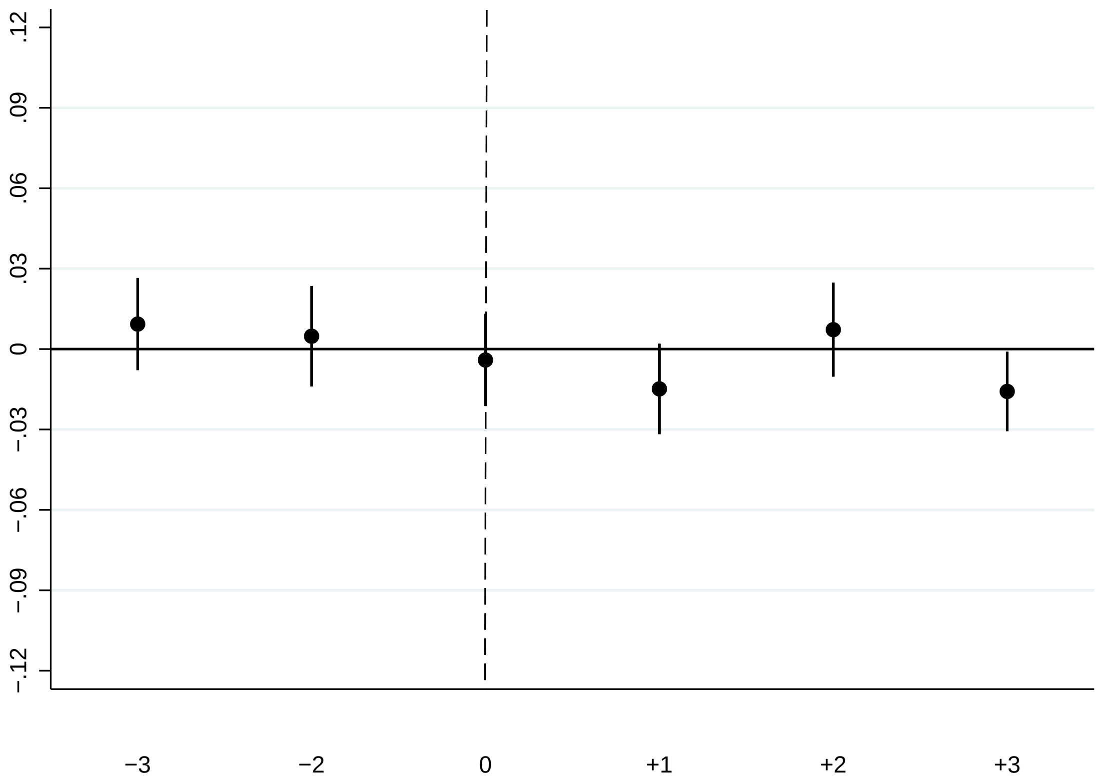
Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Figure 1: Effect of state-level mental illness parity laws on suicide rate using an event study model: CDC's Compressed Mortality File (CMF): 1998-2008



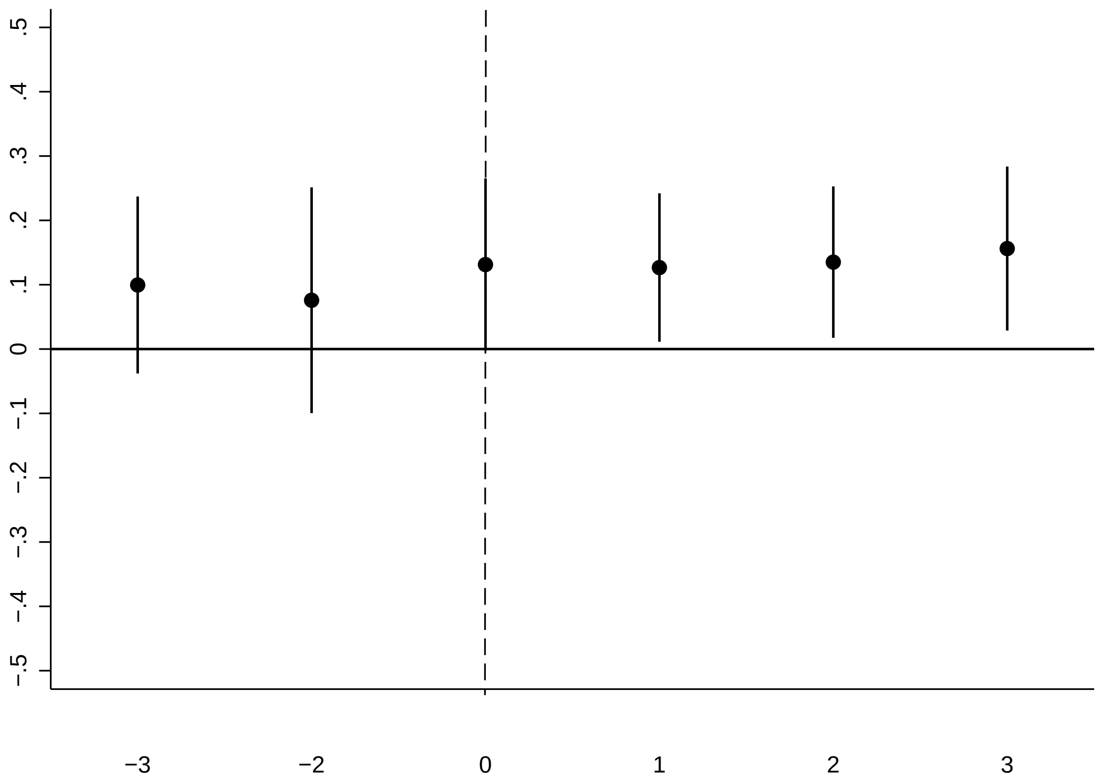
Note: Unit of obervation is state-year. Population weights applied. Event study dummy variable include 1 to 3 years pre-law and 1 to 3 years post-law, the omitted category is 3 years pre-law. All models are estimated with OLS and controls for individual characteristics, state demographics, state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. Observations for 4 or more years pre-law and 4 or more years post-law are excluded for states that passed the law. N=324.

Figure 2: Effect of state-level mental illness parity laws on propensity to report any poor mental health day using an event study model: BRFSS 1998-2008



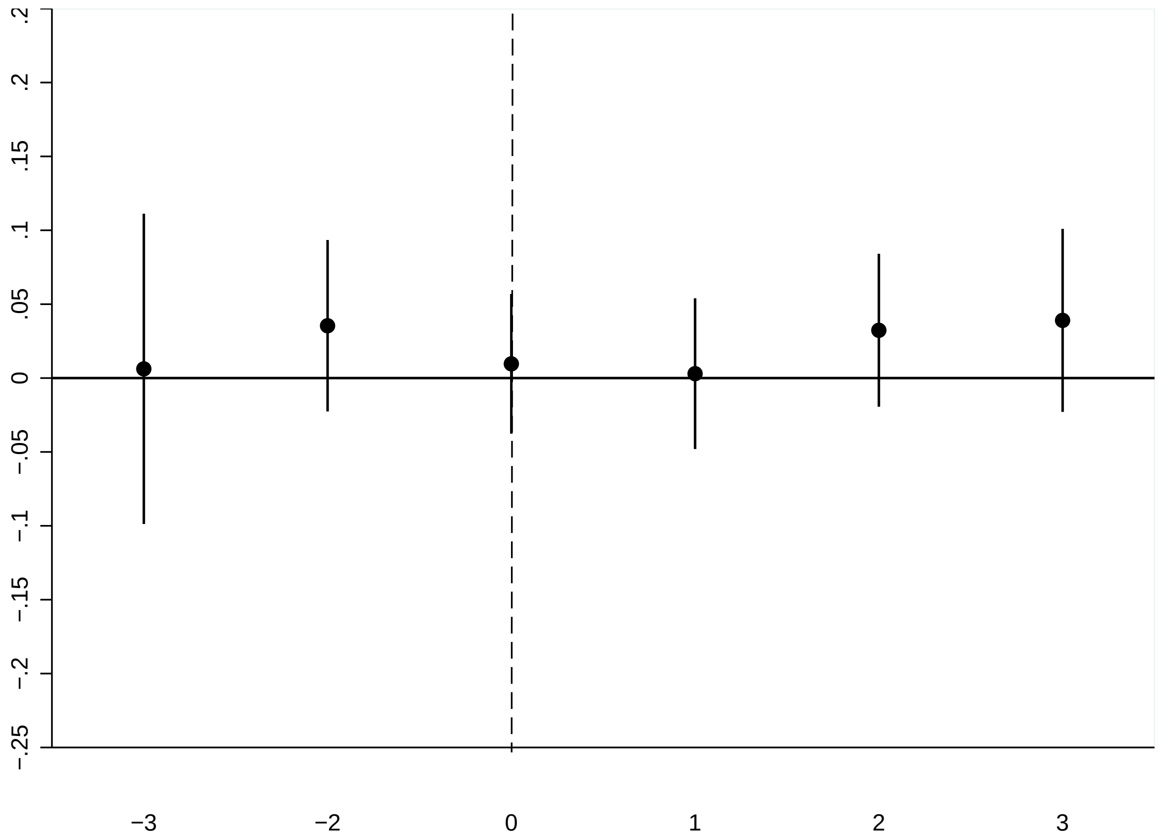
Note: Unit of observation is state-year. Population weights applied. Event study dummy variable include 1 to 3 years pre-law and 1 to 3 years post-law, the omitted category is 1 years pre-law. All models are estimated with OLS and controls for individual characteristics, state demographics, state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars.

Figure 3: Effect of state-level mental illness parity laws on college students' grade point average using an event study model: NLSY97 1998-2008



Note: Unit of observation is individual-state-year. Event study dummy variable include 1 to 3 years pre-law and 1 to 3 years post-law, the omitted category is 1 year pre-law. All models are estimated with OLS and controls for individual characteristics, state demographics, state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. N=12737.

Figure 4: Effect of state-level mental illness parity laws on college students' propensity to drop out of college using an event study model: NLSY97 1998-2008



Note: Unit of observation is individual-state-year. Event study dummy variable include 1 to 3 years pre-law and 1 to 3 years post-law, the omitted category is 1 year pre-law. All models are estimated with OLS and controls for individual characteristics, state demographics, state and year fixed effects. 95% confidence intervals account for state-level clustering and are reported in vertical bars. N=12737.

Appendix Table A1: The effect of state mental health parity laws on mental health outcomes. CDC's Compressed Mortality File (CMF): 1998-2008: Robustness tests of alternative imputed values

Imputed value:	Zero	Five	Nine
Full parity	-0.035**	-0.036**	-0.036**
	(0.023)	(0.020)	(0.019)
	[-0.065,-0.005]	[-0.066,-0.006]	[-0.066,-0.006]
Observations	561	561	561

Notes: All models are estimated with linear probability model, and controls for demographics, year fixed effects and state fixed effects, and state-specific time trends. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A2: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of excluding imputations

Outcome:	Annual Average GPA	Drop out
Sample mean	2.673	0.187
Full parity	0.079	0.004
	(0.118)	(0.881)
	[-0.021,0.179]	[-0.044,0.051]
N	8573	8573

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A3: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Heterogeneity tests with female sample

Outcome:	Annual Average GPA	Drop out
Sample mean	2.645	0.202
Full parity	0.168**	-0.015
	(0.034)	(0.507)
	[0.013,0.323]	[-0.058,0.029]
N	7140	7140

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A4: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Heterogeneity sample with male sample

Outcome:	Annual Average GPA	Drop out
Sample mean	2.532	0.193
Full parity	0.028	0.047
	(0.696)	(0.167)
	[-0.117,0.174]	[-0.020,0.114]
N	5597	5597

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A5: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of placebo laws

Outcome:	Annual Average GPA	Drop out
Sample mean	2.603	0.193
Full parity	-0.017	-0.003
	(0.632)	(0.738)
	[-0.091,0.056]	[-0.022,0.016]
N	5414	5414

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A6: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of weighting

Outcome:	Annual Average GPA	Drop out
Sample mean	2.596	0.198
Full parity	0.103*	0.001
	(0.071)	(0.950)
	[-0.009,0.215]	[-0.037,0.040]
N	12737	12737

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Sample weights applied. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A7: The effect of state mental health parity laws on interstate migration: NLSY97 1998 - 2008.

Outcome:	Movement across state
Sample mean:	0.014
Full parity law	-0.009
	(0.886)
	[-0.130,0.112]
Observations	12737

Notes: All models are estimated with linear probability model, and controls for demographics, year fixed effects, and state fixed effects. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A8: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of scope of the law

	Annual Average GPA	Drop out
Sample mean	2.596	0.198
Full parity	0.096**	0.007
	(0.048)	(0.787)
	[0.001,0.191]	[-0.042,0.055]
N	12737	12737

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Sample weights applied. Standard errors are clustered around the state. P-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A9: The effect of state mental health parity laws on college academic outcomes: NLSY97 1998 - 2008: Robustness tests of excluding small state cells

	Annual Average GPA	Drop out
Sample mean	2.592	0.011
Full parity	0.104**	0.010
	(0.024)	(0.622)
	[0.014,0.193]	[-0.032,0.052]
N	12655	12655

Notes: All models are estimated with least squares (continuous variable) or linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Sample weights applied. Standard errors are clustered around the state. P-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

Appendix Table A10: The effect of state mental health parity laws on insurance coverage: CPS-ASEC 1998 - 2008

	Any insurance	Private insurance	Public insurance
Full parity	0.004	0.014	-0.009
	(0.742)	(0.373)	(0.314)
	[-0.021,0.029]	[-0.017,0.044]	[-0.028,0.009]
N	28530	28530	28530

Notes: All models are estimated with linear probability model (binary variable), and controls for demographics, year fixed effects, and state fixed effects. Sample consists of those from 16 to 28 years old. Standard errors are clustered around the state. *P*-values are reported in the brackets. 95 percent confidence intervals are reported in square brackets. ***,**,* = statistically different from zero at the 1%, 5%, 10% level.

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