Special Education Financing and ADHD Medications:

A Bitter Pill to Swallow

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Accurate diagnosis of ADHD in children is difficult because the major symptoms, inattentiveness and hyperactivity, can be exhibited by any child. Not only is it important for children with ADHD to be properly identified and treated, but children with ADHD might be additionally harmed if resources are diverted away from children with true need. This study finds evidence of systematic differences in diagnosis and treatment of ADHD due to third party financial incentives that are unrelated to disease prevalence or severity. In some states, due to the financing mechanism for special education, schools face a financial incentive to encourage and facilitate the identification of children as having ADHD. Using variation in special education funding policies across states, we find that children living in states with financial incentives are about 15 percent more likely to report having ADHD and are about 22 percent more likely to be taking medication for ADHD. We confirm these findings using fixed effects and synthetic control methods focusing on two states experiencing a policy change over the time period studied.

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I. Introduction

Attention Deficit/Hyperactivity Disorder (ADHD) is the most common childhood mental health disorder. Accurate diagnosis of ADHD is difficult because any child may exhibit the symptoms of ADHD some of the time. Recent estimates from 2011 find that, among children ages 4 to 17 years old, 11 percent had received an ADHD diagnosis and 6.1 percent were currently taking medication for ADHD (Visser, et al., 2014). Moreover, both the rates of diagnosis and medication treatment have been increasing precipitously for decades. For example, in 2011 approximately 3.5 million children were taking medication for ADHD, which represents an increase of 28 percent (1 million more children) compared with rates in 2007. Much is not understood about the causes of this dramatic increase, and, more broadly, diagnosis and treatment patterns of ADHD in general (Visser, et al., 2014).

In this paper, we find evidence that third party financial incentives unrelated to disease prevalence or severity result in different rates of diagnosis of, and medication treatment for, ADHD. In particular, we consider whether a state-level policy that is distinct from medical recommendations can influence a child's probability of being diagnosed with and given medication to treat ADHD. Nearly half of ADHD diagnoses begin with a suggestion to parents from a child's teacher (Sax and Kautz, 2003). Thus, it is understood that schools play an important role in the identification of children who might have ADHD.

The Rehabilitation Act of 1973 and the Individuals with Disabilities Education Act of 1975 formalized the requirement that all students receive a "free and appropriate education." For students with disabilities, schools generally must provide additional services, with the cost being shared between locally-sourced funds and state funding. A principle/agent problem arises because the school has information on the needs of its student population that the state cannot verify on a case-by-case basis. States have developed various policies to provide funds to school districts for the purposes of providing special education services to children with special educational needs.

This paper documents that the type of state-level school financing for special education affects the probability a child is diagnosed with and given medication for ADHD. We explore the incentives that a school administrator might face to encourage and support the classification of students as having ADHD. In some states, a school receives additional funding that is a function of the number of children receiving special education services. It is well documented that, on average, the rates of disabilities reflect this incentive (see, e.g., Cullen, 2003; Dhuey and Lipscomb, 2011; Greene and Forster, 2002; Mahitiyanichcha and Parrish, 2005a, 2005b). While previous work has documented that these types of incentives tend to lead to higher disability rates on average, the diagnosis of ADHD may be particularly susceptible to the influence of school-level financial incentives.

The first reason why ADHD might be particularly susceptible to schools' financial incentives is that by its nature child mental health disorders are difficult to diagnose. Often ADHD is diagnosed by pediatricians and not mental health specialists (Safer and Malever, 2000). Further, the diagnostic criteria include a comparison to children's peers and require a child demonstrate the abnormal behaviors in multiple settings. Thus, a child's school is generally consulted during the diagnostic process. In fact, the American Academy of Pediatrics (AAP) clinical guidelines recommend that when making a diagnosis of ADHD, doctors should obtain information “primarily from reports from parents or guardians, teachers, and other school and mental health clinicians involved in the child’s care” (AAP 2011). In other words, ADHD is atypical in that the school has a direct role in the diagnosis of the disorder. If schools do respond to financial incentives, this will have a greater impact on ADHD than on other disabilities where the schools might refer students but are not actively involved in the process of diagnosing.

The second reason ADHD diagnosis might be particularly susceptible to the financial incentives of special education financing is that the accommodations necessary for a child who has ADHD are relatively inexpensive compared to other types of physical or mental disabilities. The typical accommodations schools make for children with ADHD include shorter in-class assignments, more frequent feedback, and extended time for tests (Schnoes, et al., 2006).[1] A school can receive financial assistance from the state government for having one additional child with ADHD qualify for special education services, but the school may only need to spend a relatively small amount to accommodate that child’s needs.[2] This is particularly true after 2001 when extended release medication became available and schools no longer had to administer stimulant medication during the school day.

This study uses pooled cross-sections from the 2003, 2007, and 2011-2012 National Survey of Children’s Health (NSCH) merged with data on state-specific legislation. We find

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[1] Federal law mandates that all children must be provided a Free and Appropriate Education (FAPE). To my knowledge, there is no specific mandate on what particular services must be provided for a child classified in each disability category. An additional aspect of the impact of financial incentives on children with ADHD could be differences in the services the school districts provide.

[2] Chambers, et al. (2003) report the total per pupil expenditures by disability category. Although it is not broken out separately, the cost for Specific Learning Disabilities (SLD) is the lowest, with an average of $5,507 total special education expenditures. This is compared with $8,126 on average for all disabilities and a high of $15,219 for children with autism.

that children living in states where schools face a financial incentive to classify students as requiring special education services are 1.6 percentage points (approximately 15 percent of the mean) more likely to report having ADHD and are 1.3 percentage points (approximately 22 percent of the mean) more likely to be taking medication to treat ADHD. We include an exploration of differences within two states that changed policies over our time period. In regression analysis, we demonstrate that estimated effects of the financial incentives are positive and statistically significant when including state fixed effects to control for time-invariant differences between states. Using a synthetic control group design, we illustrate a large impact of a policy change experienced in two states over our time period. We provide evidence that the measured effects of special education financing type are not due to some other concurrent policy differences between states. We include a series of falsification tests for child health outcomes that should not respond to the special education funding mechanism in place. Results are also robust to including controls for underlying population health and other school finance measures.

Our study design does not allow us to say what level of ADHD diagnosis and treatment is 'ideal'. Clinical researchers have methods for determining the appropriate treatment for children with mental health disorders, and this study does not contribute to that discussion, which must weigh the risks and benefits to individual patients. Rather, this study highlights strong evidence of diagnosis and treatment that is not due to medically-relevant factors at all. Both under- and over-diagnosis can be problematic. Children with untreated ADHD may be less likely to succeed in school (Fletcher and Wolfe, 2008), may experience adverse labor market outcomes in adulthood (Fletcher, 2014), may engage in risky activities (Chorniy and Kitashima, forthcoming), and may have excess risk of injuries and hospitalizations (Dalsgaard, et al., 2015; Dalsgaard, et al. 2014). Meanwhile, children inappropriately diagnosed might suffer from having taken unnecessary medication with potentially harmful side effects, as well as experience the stigma of being categorized as having a mental illness. When considering schools with particularly high rates of ADHD identification, there may also be multiplier peer effect whereby a school with many students receiving additional resources will incentivize even more students to request identification in order to ‘keep up’. Furthermore, children that have ADHD and are appropriately identified might still be harmed by higher over-diagnosis rates if the development of effective tools for diagnosis and treatment are hindered. Similarly, children with ADHD could be harmed if resources are diverted away from children with true need. Regardless of whether a child on the margin of being identified benefits from the diagnosis, clearly having a school’s financial incentives affecting a doctor’s ability to accurately diagnose and treat ADHD is neither optimal nor efficient.

II. Background

A. ADHD

According to the National Institute of Mental Health, ADHD Booklet (2012), Attention Deficit Hyperactivity Disorder (ADHD) is characterized by cognitive and behavioral deficits approximately equivalent to a three year delay in brain development. Symptoms of ADHD include “difficulty staying focused and paying attention, difficulty controlling behavior, and hyperactivity (over-activity).” There is currently no cure for ADHD, but treatments are found to relieve many of the symptoms.

A number of treatments for ADHD are indicated, including psychotherapy, behavioral therapy, and education; but currently the recommended first-line treatment for children ages 4 to 18 is stimulant medication (AAP 2011). About half of children diagnosed with ADHD take some sort of prescription stimulant, typically methylphenidate (e.g., Ritalin) or amphetamine (e.g., Adderall). Prescription stimulant medications are associated with rare but significant potential side effects including cardiovascular problems (Nissen, 2006), insomnia, stomachache, headache, dizziness, and decreased appetite (NIMH 2012). In addition, there is speculation in the medical literature that there may be adverse long-term effects of stimulant treatment for children.[3] Beyond potential harmful side effects of medication, children inappropriately diagnosed with ADHD could experience stigmatization or suffer directly from the belief that they have a mental illness.[4]

Proper identification of children with ADHD is important because untreated ADHD has been shown to lead to poor health and academic outcomes. Dalsgaard, et al. (2015) use longitudinal data from Denmark to show that children with ADHD are at a significantly higher risk of serious injury and that medication treatment can substantially mitigate this risk. Dalsgaard, et al. (2014) finds that among those diagnosed with ADHD, receiving medication treatment results in fewer hospital contacts. Choriny and Kitashima (forthcoming) find that among children who have been diagnosed with ADHD with Medicaid coverage in South Carolina, those receiving medication treatment are less likely to engage in risky behaviors.

[3] Several animal studies have suggested that exposure to stimulant medication is associated with changes in brain chemistry and cell development and function (e.g., Pardey, et al., 2012; Simchon-Tenenbaum, et al., 2015). Swanson, et al. (2007) show an initial delay in growth rates but the disparity is no longer apparent within 3 years following initial treatment. On the other hand, Harstad, et al. (2014) find no association between stimulant treatment and growth. Interestingly, Ptacek, et al. (2014) present findings from the literature supporting an altered developmental trajectory and delayed pubertal onset in children with ADHD, regardless of medication status, possibly due to disturbed circadian mechanisms commonly seen in the disorder.

[4] Currie, Stabile, and Jones (2014) consider increases in prescription stimulant treatment in Quebec due to a policy change that resulted in expanded insurance coverage for prescription medication. They find little benefit of increased medication treatment.

Children with ADHD are much less likely to succeed in school and may find that inability to pay attention causes a reduction in human capital formulation (Currie and Stabile, 2006; Fletcher and Wolfe, 2008). Stimulant medication administered to children with ADHD has been shown to lead to long-lasting positive behavioral changes (Chang, et al., 2014). Fletcher (2014) estimates that children with ADHD suffer significant labor market outcome consequences upon adulthood including a 10-14 percentage point employment reduction, a 33 percent earnings reduction, and a 15 percentage point increase in claiming social assistance. Further, Fletcher (2010) finds that the classmates of children with ADHD have lower test scores, suggesting broader social consequences of the disorder. Thus, achieving accurate and appropriate diagnosis of ADHD can help both children with and without the disorder.

B. Special Education Funding Mechanisms

To satisfy the requirement that all students receive a ‘free and appropriate education’, schools must provide additional services to students with disabilities or special educational needs. School financing policies are determined at the state level, with most states providing the bulk of finances used to provide special education services. In all settings regarding special education services, there is a principle/agent problem where the school has information on the needs of its student population that the state cannot verify on a case-by-case basis.

While each state has a unique set of rules governing special education funding, these policies can be broadly classified by whether they provide reimbursement based on the number of students identified as requiring services versus on the total population of students. The latter is most typically called “census-based”.[5] In some states, the special education financing

[5] Dhuey and Lipscomb (2011) refer to these states as having a “capitation” method, borrowing the term from the health insurance setting with an HMO receiving payment per population rather than per services rendered.

mechanism attempts to redistribute resources from lower to higher need districts, usually based on the underlying wealth of the population rather than the underlying incidence of disability. Thus, there is likely some heterogeneity in the magnitude of the incentives based on population wealth or poverty levels.[6]

It should be noted that typically ADHD is grouped in a category of disabilities referred to as “Other Health Impairments” or OHI. When multiple weights are assigned for funding, OHI typically is assigned a weight above the lowest level. Thus, schools may find that ramping up the number of children requiring special education services for ADHD provides more revenue than other disabilities, for example learning disabilities. For this study, we group together all funding mechanisms that provide some dollar value incentive for diagnosis.[7] The Appendix provides detail on each state’s policies.[8]

III. Data and Econometric Framework

The central question of interest is whether the special education financing method used in a child’s state affects his/her probability of being diagnosed with ADHD and receiving medication treatment for ADHD. To address this question, this study uses pooled cross-sections from the 2003, 2007, and 2011-2012 National Survey of Children’s Health (NSCH), conducted

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[6] A further complication is that some states impose a predetermined cap on the number of students identified as requiring special services that can be used in determining funding levels. Clearly there is a strong incentive for a school district to meet and not exceed this cap. Over the time period studied, only North Carolina has a cap in place.

[7] Appendix Table A3 presents results for finer delineations. Results should be interpreted with some caution since some coefficients are estimated from policies in just one or two states.

[8] Much of this discussion is informed by the work of Parrish, et al. (2003) and Ahearn (2010). We also consulted the state statutes for each state.

by the National Center for Health Statistics.[9] The NSCH is a household-level survey. The benefit of using household data, rather than data gathered by schools, is that we can be assured that the numbers are not somehow being altered to reflect the financing incentives. For example, a school district may classify children as having ADHD and requiring special services, while in practice the child does not experience any differential treatment. In the NSCH, the survey respondent is typically a parent, and it is unlikely that the parent is aware of the intricacies of state school financing policies. Furthermore, we are able to measure not just identification as having ADHD, but also whether prescription medication is being used to treat ADHD. Thus, even when measured at the individual child level completely outside of the school setting, we find that children are being administered prescription medication for ADHD at differential rates depending on the schools' financial incentives.

[9] The data were provided by the Data Resource Center and Child and Adolescent Health Measurement Initiative (CAHMI):

2003 National Survey of Children's Health. Maternal and Child Health Bureau in collaboration with the National Center for Health Statistics. 2003 NSCH Stata Indicator Data Set prepared by the Data Resource Center for Child and Adolescent Health, Child and Adolescent Health Measurement Initiative. www.childhealthdata.org

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Another advantage of the NSCH data is that they are designed to be representative at the state level, but include weights to adjust representativeness to be at the national level. Thus, throughout the analysis we include these as analytic weights to reach a nationally representative sample. Because one of the two states that made policy changes over our time period (West Virginia) is not populous, it is particularly advantageous that the data are representative, and suitable for analysis, at the state level.

A. Means

We restrict our attention to children ages 6-17 to ensure that most children were enrolled in school in the previous year. Although the data include an indicator for the type of school attended (e.g., public or private), this choice could be endogenous to the state special education funding mechanism, so we do not restrict the sample based on public school attendance. We exclude children living in Hawaii from our analysis.[10] As shown in Table 1, the final sample includes 182,706 children over three years. Utilizing the sample weights this implies a population of approximately 43-47 million children in each survey year. All data are reported by an adult household member. Table 1 presents the sample means for the full sample pooled together and individually by survey year.

[Table 1]

[10] In Hawaii, the funding mechanism changed in 2006 from having no separate funding to one with weights. Ahearn (2010) classifies Hawaii as no separate funding because special education funding is rolled into general education funding. However, because weights are attached while calculating funding by severity of disability, we believe Hawaii does have some financial incentive in the latter two time periods. However, given that Hawaii is one large school district, and that it cannot be readily classified, we have chosen to exclude it from our analysis. We observe a fall in diagnosis and medication rates in 2007 but a rise in both rates 2011-2012.

Approximately 70.6 percent of all children live in states where there is some incentive for the school district to identify students as requiring special education services. This fraction drops to 67.9 percent in the final year of our sample because, as described below, New Jersey switched to a census-based classification system. First, we see that on average about 10.7 percent of children ages 6-17 in the US have ever received an ADHD diagnosis, with the rate growing from 9.2 percent in 2003 to 12.1 percent in 2011-2012. About 6 percent of children are currently taking medication to treat ADHD, with that rate growing from 5.2 percent in 2003 to 6.9 percent in 2011-12. These levels of ADHD observed in the population are consistent with measures of ADHD prevalence from the National Health Interview Study (see Evans, Morrill, and Parente, 2010) and previous estimates using the NSCH data (Visser, et al., 2014). Table 1 also presents the means of demographic characteristics included in the regressions. About 61.4 percent of the sample are non-Hispanic white, about 64.6 percent have private health insurance, and 27.8 percent report family income above 400% of the federal poverty limit (FPL).

Table 2 presents the broad groupings of states into those where a financial incentive is in place or not. In the top row, we see that among the 13 states that had no financial incentive over all years of our data, diagnosis and treatment rates are rising over time. But when compared with states in the second row that had a special education funding mechanism that created a financial incentive for diagnosis, the latter states have substantially higher rates of diagnosis and medication usage in every year. When comparing the top two panels of Table 2, we see that in 2011-2012 children in states where school districts faced a financial incentive for identification had, on average, a 2.4 percentage point higher risk of ever having been diagnosed with ADHD (12.9% versus 10.5%), or about a 23 percent higher rate than those in the no incentive states. When considering whether the child is currently taking medication for ADHD, in 2011-2012 states with financial incentives also have 2.4 percentage point higher (7.7% versus 5.3%), or about a 45 percent higher, rate, on average.

[Table 2]

State policies might arise from differences in the underlying population. One approach to controlling for time-invariant state characteristics is to estimate the effects of incentives in states that changed their policies over our sample period. We have only two such states in our sample: New Jersey and West Virginia. In New Jersey, in 2008 the funding mechanism was changed from multiple weights to census-based. We observe the probability of being 'ever diagnosed' with ADHD fell by 12.5 percent (from 9.6 percent to 8.4 percent) between the 2007 and 2011-2012 samples. We note that while the medication treatment rate in New Jersey also fell, the baseline level of medication treatment in New Jersey is well below the average rate for the other states.

West Virginia similarly changed from a single-weight formula to having "no separate funding" in 2008, but in that case the new formula was phased in over five years with districts receiving a portion of the differential between the two formulas. In West Virginia the probability of having ever been diagnosed with ADHD fell from 14.1 percent to 13.4 percent, even at a time when diagnosis rose in other states. Similarly, the rate of medication to treat ADHD fell from 8.7 percent in 2007 to 8.5 percent in 2011-12, while the rates of medication continued to rise in the other states. Because the latter policy was phased-in, and because only two states changed policies, the main results are reported without state fixed effects.

Figure 1 graphically illustrates these same statistics as in Table 2. Here we see that both diagnosis and medication treatment rates are rising over time in states that did not change policies and that states with an incentive always have higher rates than those without an incentive. When comparing with the two states that changed policies between 2007 and 2011-12, we see that both diagnosis and medication treatment rates fell. We explore this further below using state fixed effects and synthetic control group methods.

[Figure 1]

B. Exploration of Policy Changes

Theoretically, current diagnosis of ADHD will reflect the incentives in place during that school year. However, in practice, we suspect there is some ‘stickiness’ in ADHD diagnoses such that once a child is diagnosed, they are much more likely to continue being labeled has having ADHD. Some children diagnosed with ADHD eventually recover and do not have ADHD as adults (NIMH 2012). Thus, it is possible that a ‘dropped’ diagnosis reflects recovery and not a false positive initial diagnosis.

Here, we model the probability of having a current ADHD diagnosis to be separable into the sum of the risk of having had a previous diagnosis plus the risk of having a new diagnosis. In equation (1), we represent the risk of a new diagnosis as ν, which can be identified in the data as having an age of diagnosis equal to current age (or one year younger). The probability of having a diagnosis ‘dropped’ is represented by δ and is measured as having ever had ADHD but not currently diagnosed with ADHD.

$$(1)\ \Pr(ADHD\ Current_{ist} = 1) = \Pr(ADHD\ Ever_{ist} = 1) * (1 - \delta) + \nu$$

When the financial incentive is removed, as it was in New Jersey and West Virginia, we expect an increase in the rate of dropped diagnoses, δ. However, in practice, in the first few years after a policy is removed, having a noticeable increase in δ would be surprising as it would take time for schools to appreciate the change in incentives and overly large values would raise suspicions. In the unweighted data, we observe 19 children in NJ and 27 children in WV that had a “dropped” diagnosis in 2007. In 2011, we see only 18 children in NJ and 31 children in WV with a dropped diagnosis. In results not shown, when considering states that did not change their policies, we observe a statistically significant higher drop rate, on average (population weighted), of 1.7 percent in the incentive states versus 1.2 in the non-incentive states.

When the financial incentive is removed in New Jersey and West Virginia, we would anticipate a decrease in the rate of new diagnoses (ν in equation 1) for all age groups. If the older ages had been exposed to excess identification, then a larger fraction of all new diagnoses should be to the youngest children. Without knowing more about the mechanisms through which financial incentives affect ADHD diagnosis, it is difficult to predict how new diagnoses vary by age groups for states that did not change their incentives. It may be that the incentive is strongest for younger children who will be in school for longer, but it may also be that the cumulative effects of exposure to the incentive means that older children will finally cross the threshold for identification and experience the largest effects of the incentive.

In the 2011/12 data, a variable was included that measured the age of diagnosis for those who were ever diagnosed with ADHD. Unfortunately, we cannot compare changes in this variable since it is only available in the last year of our data. We define a new diagnosis as one that occurred either at the current or previous year of age. Mechanically, on average, younger children are much more likely to have a ‘new’ diagnosis, but we can consider how the patterns of new diagnosis differ between states that did not change policies and the two states that experienced a policy change. Figure 2 illustrates the fraction of the full population that received a new diagnosis separately for three age groups, 6-9 years old, 10-13 years old, and 14-17 years old. In the states that did not have an incentive in place throughout the time period, we observe a declining rate of new diagnosis, as predicted. When comparing those states with the group of states that always had a financial incentive in place, the main difference is seen in a much higher recent diagnosis rate among the youngest age group. Interestingly, in the (population weighted) average of New Jersey and West Virginia, we do observe a substantially lower new diagnosis rate among the oldest age group. The youngest age group still experienced a higher rate of new diagnosis than states that never had an incentive, although recall that West Virginia phased-in their program. Figure 2 does suggest that a higher fraction of new diagnoses are indeed among the youngest age group in the states that removed an incentive. In addition, Figure 2 provides some evidence that the youngest are most susceptible to financial incentives. We explore this possibility further in a regression context in Table 8.

[Figure 2]

Next, we utilize information on perceived severity of ADHD to provide further evidence of gaming behaviors by schools. The 2007 and 2011-2012 NSCH data include a variable measuring whether ADHD is mild, moderate, or severe. We use this information to explore whether the threshold for identification of ADHD shifted downwards or whether perceived severity increases throughout the distribution of ADHD-related symptoms.

On the one hand, we might expect that the perception of the ADHD spectrum is constant, but the threshold (to parents) for identification is moved “downward” due to the influence of the school. In this case, the marginal ADHD diagnosis would be less severe. Conditional on having ADHD, we should see a higher fraction of mild or moderate cases relative to severe cases. Furthermore, we would expect no change in the probability of having severe ADHD overall, and for the full effect of the policy to be on higher rates of mild and moderate ADHD. On the other hand, if a medical professional’s assessment is based partially on school reports, then it may be that the entire ADHD spectrum is shifted towards ‘more severe’, since doctors will be getting information that the ADHD symptoms are worse. In this case, we would expect 'moderate/severe ADHD' to be similarly affected by the policy and the fraction of children with ADHD labeled as 'moderate/severe' to be constant. Figure 3 provides evidence of the former mechanism. We observe that rates of mild and moderate ADHD rise between 2007 and 2011/2012 for the states that did not change incentives. In addition, we observe that the rates of mild ADHD are about 40 percent higher in states that have a financial incentive for identification, while rates of severe ADHD are nearly identical. Interestingly, we observe that in the two states that removed their financial incentive, the rate of severe diagnosis remained basically flat while the rates of mild and moderate ADHD both dropped. Thus, these results are consistent with the financial policy affecting the threshold of identification rather than the perceived severity of all ADHD cases.

[Figure 3]

C. Framework for Regression Analysis

The dependent variable in the main regression equation is an indicator for either a child having received an ADHD diagnosis or for currently taking medication to treat ADHD. The outcome is regressed on a vector of child and family characteristics and a set of indicators for whether the special education funding mechanism in that state provides a financial incentive for schools. The dependent variables are dichotomous, so we estimate using a linear probability model. Estimates from a Probit regression are presented in Table 8 and are very similar. The main regression equation is:

$$(2)\ \Pr(ADHD\ Outcome_{ist} = 1) = \alpha_0 + X_{ist}\beta + FinancialIncentives_{st}\gamma + \eta_t + \theta_s + \epsilon_{is}$$

We observe child *i* in state *s* at time *t*, with the vector of financial incentives defined at the state x time level. We include controls for the child's age, gender, race/ethnicity, and family income.[11]

Because only two states changed policies over this time period, we present the main results without including the state fixed effects. We then confirm robustness to including state fixed effects in the model, which results in identification just from New Jersey and West Virginia. As a further test, we construct a synthetic control group in the manner of Abadie, Diamond, and Hainmueller (2010).

The pooled cross-section without state fixed effects identifies the average differences across states, but might be confounded by unobserved differences between states such as the underlying morbidity of the population or the culture and intensity of medical services. When including fixed effects, the estimates are instead identified from states that changed policies holding all time invariant characteristics of the two states with the policy changes constant. However, the policy change may have been made because of some discontent with the initial policy (see, e.g., Augenblick, et al., 2008), and states making changes might have had different underlying trends in special education identification rates. Further, transition years might have distinct effects on the diagnosis of ADHD that may differ from the average effects of the policies in steady state.

An additional reason the estimated effect of the financial incentive might differ when state fixed effects are included is that these policies likely result in persistent classifications once a child receives a disability diagnosis. In other words, children identified as requiring services would not likely be "dropped" right when the incentive structure changes. Rather, we would

[11] Specifications including the source of health insurance for the child yield similar estimates. Unfortunately, information about family structure, including the presence of the biological mother and father, is not available in the 2003 and 2007 data.

expect the new policies to really affect those just entering schools or those not yet classified as requiring services. Finally, when a state chooses a policy it will certainly take into account the underlying morbidity of the population, as well as the culture towards the identification and treatment of children with disabilities generally.

IV. Results

A. ADHD Diagnosis and Treatment

The sample means reported in Table 2 and Figure 1 indicate large differences in ADHD diagnosis and medication treatment rates by financial incentives. We next explore whether these differences are found in individual-level data when demographic characteristics are included. The first column of Table 3 presents the estimates from a linear probability model regression of the probability of having received an ADHD diagnosis on special education funding incentives and a host of demographic characteristics. All standard errors reported are clustered at the state-level to account for within-group dependence (see Bertrand, et al., 2004).

[Table 3]

In Column 1, Table 3, we see that, holding individual characteristics constant, a child living in a state with a financial incentive for identification is 1.6 percentage points more likely to be ever diagnosed with ADHD, which is about 15 percent of the mean of 0.107. The second column of Table 3 presents estimated coefficients from a regression on whether the child is taking medication to treat ADHD. Here, we see a 1.3 percentage point higher rate of treatment in states with financial incentives, which is approximately 22 percent of the mean of 6.0 percent. We interpret this as evidence that the incentives for identification inherent in special education funding mechanisms have led to higher rates of diagnosis and treatment of ADHD.[12]

In Table 3, we also see that, consistent with the prior literature, boys are much more likely to be diagnosed with and treated for ADHD. Similarly, as children age they have higher probabilities of having ADHD. Also in line with prior findings, non-Hispanic whites have the highest rates of ADHD, even controlling for family income. Those with family income below 133% of the Federal Poverty Limit have the highest rates of ADHD diagnosis and treatment.[13] While we see effects of various demographic characteristics on the probability of diagnosis, these differences do not explain the state-level variation in diagnosis rates.

B. State Fixed Effects and Synthetic Control Group Methods

Next, we estimate equation (2) with the inclusion of state fixed effects. Table 4 presents a parallel set of estimated coefficients to Table 3, except here state fixed effects are included. While the inclusion of state fixed effects allows us to control for any time invariant differences across states, with only two states changing policies over our time period inference may be problematic. Appendix B describes the results of a nonparametric permutation test for inference.[14] The results of this exercise support the main conclusion that financial incentives for

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[12] As an additional robustness check, we dropped each state and reestimated the specification in Column (1). When there are no state fixed effects, the only influential state was California. When that state was excluded the estimated coefficient was 0.012 (0.007), p-value 0.072.

[13] In results not shown, including the child's source of health insurance yields nearly identical estimates for the impact of the financial incentives. However, the poverty measures are no longer statistically significant, as these variables are highly collinear. We find that diagnosis and treatment rates are highest among those children who have public health insurance. We chose to exclude health insurance status as it could be endogenous.

[14] Conley and Taber (2011) illustrate that in settings with a small number of policy changes standard errors are not estimated consistently and rejection rates are generally too low. The exercise conducted

identification are associated with positive and significant increased probabilities of ADHD diagnosis and medication treatment. As shown in Column (1) of Table 4, when state fixed effects are included, the estimated coefficient on ever having an ADHD diagnosis is 2.6 percentage points (about 24 percent of the mean). When considering the outcome of currently receiving medication to treat ADHD, the estimated impact of the financial incentive is nearly identical with the inclusion of state fixed effects.

[Table 4]

Next, we explore a synthetic control group method, described in Abadie, Diamond, and Hainmueller (2010). The idea is to identify states that are most similar to the treatment states from among a large group of potential control states. Here we include a separate analysis of New Jersey and West Virginia. Appendix Table C1 reports the weights assigned to each state used to create the synthetic control state. This is done separately for each outcome, 'ever diagnosed' and 'ADHD medication', and for each treatment state, New Jersey and West Virginia. To conduct this exercise, we collapse the data to the state-level (using population weights). We then restrict attention only to states that had an incentive in place in 2002 and 2006, with potential control states being those that did not remove the policy by 2010.

Table 5 presents the population-weighted means for the treatment state, the group of potential control states, and the synthetic state. Panel A presents the results for New Jersey. Column (1) is the raw means, as shown in Table 2. Column (2) is the weighted means of the states that always had an incentive in place, again as shown in Table 2. For Column (3), we present the results from the synthetic control state that provides a theoretically better

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here is similar to the tests in Ebenstein and Stange (2010) and is based on Fisher's randomization tests (Fisher 1935).

counterfactual for what would have happened in New Jersey had the policy not been changed in 2008. We observe that the means in 2003 and 2007 are identical between New Jersey and the synthetic New Jersey, but that for the 2011-12 cohort the rate of ADHD diagnosis is much higher in the synthetic control state. When considering medication treatment for ADHD, we note that New Jersey actually had a quite low medication treatment rate in 2003 and 2007, which made finding appropriate comparison states difficult. As shown in Appendix Table C1, only two states contributed to the synthetic New Jersey when considering medication treatment (Colorado at 88% and Nevada at 12%). For this outcome, we see that medication treatment for ADHD is actually slightly higher than the synthetic control group in 2011-12.

[Table 5]

Panel B of Table 5 presents a parallel exercise for West Virginia. Again, we can see that the synthetic control group is virtually identical to West Virginia in 2003 and 2007. In 2011-12, West Virginia had lower rates of ADHD diagnosis and treatment relative to the synthetic control group. Because of concern over inference in difference-in-differences settings with few treated groups (see Appendix B), the remaining tables focus on the estimates using cross-state variation.

C. State-Level Policies and Population Characteristics

Whether or not state funding for special education is allocated by "census" is only one aspect of state policies that might affect a child's probability of being identified as having a disability requiring services. For example, Winters and Greene (2011) show that special education vouchers affect the identification of disabilities. Similarly, accountability standards that exempt some or all students with disabilities induce higher identification rates (e.g., Figlio and Getzler, 2006). Bokhari and Schneider (2011) show that school accountability laws are associated with significantly higher rates of ADHD medication usage among school aged children but not adults. Kubik (1999) illustrates how Supplemental Security Income (SSI) eligibility rules increase the detection and treatment of medical problems among low-income children. A key assumption of the econometric model is that there are no contemporaneous policies (or policy changes, in the models including state fixed effects) that also affect ADHD. To confirm that the special education financing result is not spuriously related to some other state-level policy or some underlying population characteristics, we provide a series of robustness checks.

Because of concern that the special education funding incentive might be correlated with other school finance policies that also affect children, we add to the main specification reported in Table 3 several measures of school funding.[15] The additional variables are student population (in millions), the percent of revenue from local sources, the total federal revenue per student (in thousands), the percent of expenditure on instruction, and the total expenditure per pupil (in thousands). These are each measured at the state-by-year level. Table 6 presents estimates of equation (2) that are parallel to those presented in Table 3, except that here a host of alternative state-level policies and characteristics are included.[16]

[Table 6]

As seen in the first row of Table 6, the estimated effect of the financial incentive due to special education funding is similar to that reported in Table 3 and always positive and

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[15] Data on revenue and expenditures is provided by the National Center for Education Statistics, Elementary/Secondary Information System. Tables are publicly available at: https://nces.ed.gov/ccd/elsi/, [accessed April 2015]. Data are derived from the Common Core of Data (CCD).

[16] All covariates from Table 3 are included in the model; estimated coefficients from the full specification are available upon request. Note that children living in the District of Columbia are excluded from Table 6 because of missing data on the mental health parity laws. Parallel estimates including state fixed effects are similar and are available upon request.

statistically significant. To the extent that school resources are a function of the underlying population wealth, which might in turn be related to students' health, it is perhaps surprising that we see little relationship between these school funding variables and ADHD. We do observe that the size of the student population is negatively related to ADHD diagnosis. We find no evidence that school funding generally explains the relationship between special education funding incentives and ADHD, at least when measured at the state level.[17]

Another possible explanation for our results is that the population in states with a special education financial incentive is, on average, less healthy. There could be environmental factors that influence poor health, differences in the technology or culture surrounding medical care, or differences in the health care market. If there is a stronger demand for medical treatment, then perhaps the special education funding mechanisms are reflecting preferences of the populations. Although the state fixed effects control for all time invariant differences across states, there might still be some shift that happened concurrent to the special education funding policy change. To verify that these concerns are not confounding our results, we include two measures of the health care market: the state Medicare spending per enrollee (in thousands of dollars) and the state Medicaid spending per enrollee (in thousands of dollars).[18] The latter measure includes

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[17] In results not shown, when the special education financial incentive dummy variable is interacted with the spending variables, we find weak evidence that larger student populations are associated with stronger incentives (only when 2003 data are included). It is outside the scope of this study, but there may also be a non-linear impact "peer effect" whereby having a large cohort of students receiving special education services induces parents to request additional resources for their own child.

[18] Data on health expenditures by state of residence is provided by the Centers for Medicare and Medicaid Services (CMS) at: http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsResidence.html, [accessed May 2015]. The data are derived from the National Health Expenditure Survey. Centers for

Medicaid spending on the poor and aged, which represents the largest portion of Medicaid spending. We do see that, on average, higher Medicare spending per enrollee is associated with higher ADHD diagnosis and treatment rates. While this suggests that something about the health care marketplace or underlying population morbidity might be associated with ADHD rates, we find no evidence that the relationship between special education financial incentives and ADHD can be explained by differences in population health or the health care market. The specification also includes the cut-off for Medicaid eligibility for children ages 6-18.[19] Access to Medicaid may allow a child to receive medical care and lead to ADHD diagnosis and treatment, although we find no evidence of a relationship, on average.

The final set of state-level measures concerns the treatment of mental health for insurance purposes. States regulate group health insurance policies. Not only might mental health coverage directly affect ADHD diagnosis and treatment, but these laws might also proxy for the cultural norms of mental health treatment and the underlying population characteristics. States

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Medicare & Medicaid Services (2011). *Health Expenditures by State of Residence.* Retrieved (May 2015) at http://www.cms.gov/NationalHealthExpendData/downloads/resident-state-estimates.zip

Note that in 2010 the National Health Statistics Group undertook a revision of the National Health Expenditure Accounts. Thus, we are using data on expenditures in 2009 to approximate health expenditures in 2010 rather than impute a cost growth. Actual data from 2002 and 2006 are used. The spending per enrollee is the summation of all 10 categories of spending and includes all age groups.

[19] Medicaid income eligibility limits for children ages 6-18 are found at: http://kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-children-ages-6-18/, [accessed July 2016]. We used data for January 2002, July 2006, and January 2011. We imputed 100% for Tennessee for the 2002. Kaiser Family Foundation also provides data on CHIP eligibility thresholds, where applicable. In results not shown, this variable and an indicator for "N/A" are not significantly related to ADHD outcomes. In addition, including these variables in the specifications did not affect the estimates on other variables in the model.

are grouped into four main categories of mental health parity legislation for each year: (1) full parity for mental health, (2) a minimum mandated mental health benefit, (3) a mandate to offer at least some mental health coverage, or (4) no mental health mandate law.[20] In Table 6, we see no statistically significant relationship between state health insurance mental health parity laws and children's probability of ADHD diagnosis or treatment. In summary, in Table 6 we see that the measured effect of special education financial incentives is robust to including a host of state-level measures on school funding, population health, and the health care marketplace.

D. Alternative Health Conditions

Next, we provide a further test of whether the special education financial incentive is simply reflecting state-level differences in underlying population health, environmental factors, cultural attitudes towards health, or the health-care marketplace by considering several alternative health outcomes. We estimate a version of equation (2) where the dependent variable is an alternative condition that should not be affected by the financial incentive. The first column repeats the estimates for ever having an ADHD diagnosis for comparison. First, we consider whether the child has hearing or vision problems. These two disabilities are related to having a direct need for special education services but are less likely to be influenced by school policies. In Table 7, Column (2) we see no association between financial incentives and hearing or vision problems.

[Table 7]

[20] The states all have unique laws, coverage, and exceptions that are not reflected in this exercise. Data on mental health parity laws is provided by the National Conference of State Legislatures (NCSL) on their website at: http://www.ncsl.org/research/health/mental-health-benefits-state-mandates.aspx, [accessed April 2015]. Data are not provided for the District of Columbia. Full data on the definitions and classifications used in this exercise are available from the author upon request.

Next, we consider three conditions that would typically not require special services to be provided: depression/anxiety, diabetes, and asthma. All three conditions have no statistically significant relationship with special education funding incentives. It is interesting to note the similarities and differences in the estimated coefficients on the covariates between ADHD and the other health outcomes considered here. The financial incentive has a large and robust relationship with ADHD diagnosis and treatment, but no significant association with the other outcomes. However, we do observe many similarities in the estimated coefficients on the other covariates in the model when comparing between health outcomes. The rate of ADHD diagnosis is most similar to depression/anxiety and asthma. We see growth in the rates of all health conditions over time and all conditions except diabetes disproportionally affect boys. Interestingly, differences by race are similar to ADHD for hearing/vision disorders and depression/anxiety. However, non-Hispanic black children are significantly more (not less) likely to have asthma, and there is no statistically significant difference in the probability of asthma diagnosis between Hispanic and non-Hispanic white children, all else equal. All conditions, except diabetes, are most prevalent among those with lower family incomes. Thus, while the patterns of these conditions follow ADHD along demographic characteristics, they do not have a similar association with the state special education funding mechanism. Thus, we again find support that the financial incentive is not acting as a proxy for some underlying population characteristic that influences ADHD diagnosis and treatment rates.[21]

[21] One might also predict that the financial incentive affects learning disabilities in a similar way to ADHD, although perhaps with a smaller effect. Learning disabilities are often identified and diagnosed by school professionals, see: https://ldaamerica.org/resources/guides-booklets/, [accessed July 2016]. In results not shown, the estimated coefficient on learning disabilities in a parallel specification is not statistically significant (-0.0002, s.e. 0.004, mean 0.116).

E. Heterogeneous Effects by Child Characteristics

Table 8 explores whether the effects of the incentives vary for different demographic groups. Here, the financial incentive dummy variable is interacted with one or more demographic group. The reference group is specified in parentheses for each panel. Thus, the first coefficient in the panel is the main effect for the omitted group. The subsequent coefficients are the estimated difference between the omitted group and the group specified. All specifications include the individual-level covariates reported in Table 3 (except where collinear). Panel A repeats the baseline results for reference.

[Table 8]

First, we consider whether the financial incentive has a differential effect for boys and girls in Panel B of Table 8. Recall that ADHD diagnosis and treatment rates are significantly higher for boys than for girls; Table 3 indicated that boys are 8.6 percentage points more likely to be ever diagnosed with ADHD and 5.1 percentage points more likely to be receiving medication for ADHD. In Panel B of Table 8, we see that financial incentives are associated with a 0.9 percentage point higher rate of ever having an ADHD diagnosis for girls and an additional 0.8 percentage point higher rate for boys, although neither estimate is statistically significant. When considering medication treatment in Column (3), the main effect for girls is statistically

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While the 2007 and 2011/2012 NSCH data also provide a measure of having an Individualized Education Program (IEP), a student needs only to qualify for some special education services, not necessarily to have an IEP, for the school to receive the additional funding. The National Center for Education Statistics (NCES) reports that the percent of students served by special education services was 13.6 percent in 2006-2007 and 12.9 percent in 2011-2012, see: https://nces.ed.gov/fastfacts/display.asp?id=64, [accessed July 2016]. The mean IEP rate in the NSCH data is 11.1 percent in 2007 and 11.3 percent in 2011-2012. In a regression on IEP designation, the estimated coefficient on special education incentives is negative and not statistically significant (-0.011, s.e. 0.009).

significant but the additional impact for boys is not. Thus, although the sign of the coefficient on the interaction term is large and positive, we do not find any statistically significant evidence that the financial incentives disproportionally affect boys relative to girls.

As discussed in Section III.B., while diagnosis and treatment rates rise as children age, it is not clear *a priori* whether younger or older children should be more affected by financial incentives for identification. The raw means presented in Figure 2 suggested that the youngest age group would be disproportionally affected. However, in Table 8, Panel C, we see that the impact of financial incentives on ADHD diagnosis and treatment is not statistically significantly different for children ages 10-13 or ages 14-17 relative to children ages 6-9. While the raw means did indicate that the youngest children are most susceptible to the influence of special education financial incentives, we fail to detect a statistically significant difference in the regressions.

In Panel D of Table 8, we see that the financial incentive does not appear to have a statistically significant differential effect by racial/ethnic group with one exception. We do see a large and statistically significant point estimate for the group of children classified as 'Other Race/Ethnicity', indicating a potentially stronger effect of the policy for that group. Next, in Panel F of Table 8, we see that the effect of the financial incentives is strongest for those children whose family's income is between 133% and 400% of the federal poverty line (FPL), although the differences are not statistically significant when considering medication treatment. This is not surprising since many states give a larger multiplier for schools with low income populations, so those children might be disproportionally affected by the financial incentive.[22]

[22] See Cullen (2003) for a discussion of this in Texas.

The final two rows of Table 8 report two additional sensitivity tests. First, Panel G shows that estimates from a Probit model are nearly identical to the baseline linear probability model estimates presented in Panel A for ADHD diagnosis and medication treatment. Finally, point estimates are similar when population weights are not applied but are no longer statistically significant.

V. Conclusions

Substantial differences exist in the probability of being diagnosed with ADHD based on whether the child resides in a state with a special education funding mechanism that creates an incentive for diagnosis. An effect of similar magnitude is found when considering a child's probability of receiving medication treatment for ADHD. This is clear evidence of non-medically relevant legislation impacting medical diagnosis and treatment of ADHD. These results use data from the National Survey of Children's Health (NSCH), which is not collected through schools. Therefore, we are not relying on a school's self-reports of the total number of students requiring special education services, but rather we look to a household-level survey that documents childhood diseases.

This study does not provide direct evidence on whether ADHD is over-diagnosed or under-diagnosed, nor whether prescription stimulants are the correct course of action in a given circumstance. Indeed, children may benefit from the extra services they receive through an Individualized Education Program (IEP) or under Section 504 (e.g., Hanushek, et al., 2002). Further, stimulant medication can have long-lasting positive behavioral changes for children with ADHD (Chang, et al., 2014). Classmates of children with ADHD might also benefit (Fletcher, 2010). However, the allocation of academic resources should be based upon child needs and potential benefits, not schools' financial incentives. In addition to resources potentially being diverted from children with true need, identifying children as having ADHD when they do not inhibits research on the accurate diagnosis of ADHD and effective treatments.

This study finds that in states where schools have a financial incentive to identify children as requiring special education services children have about a 15 percent higher probability of having been diagnosed with ADHD and an 22 percent higher probability of taking medication for ADHD. The 2011-2012 NSCH data represent about 47 million children ages 6 to 17. Using conservative estimates, this implies around 800 thousand children were diagnosed based on this non-medically relevant policy. Similarly, over 650 thousand children were taking medication for ADHD due solely to the financial incentives for special education classification. Prior literature has found that when special education funding mechanisms switch to a census-based non-incentive method average rates of identification drop by about 10 percent (Dhuey and Lipscomb 2011; Mahitivanichcha and Parrish 2005a). According to statistics from the National Center for Education Statistics, the category that includes ADHD (Other Health Impairments) accounted for about 12 percent of all disabilities in 2011-2012.[23] Thus, ADHD diagnosis does seem to be disproportionally affected by the incentives, but is likely not the only disability affected by special education financial incentives.

This study finds robust evidence that medication is being prescribed as a result of schools' financial incentives. This contributes to the growing literature indicating medically inappropriate diagnosis and treatment of ADHD (e.g., Evans et al., 2010; Elder, 2010). Although it may not be surprising to find that schools are responding to incentives, the ability of medical professionals to properly understand and treat ADHD may be hindered by non-objective

[23] U.S. Department of Education, National Center for Education Statistics. (2015). *Digest of Education Statistics, 2013* (NCES 2015-011),Chapter 2, available at: https://nces.ed.gov/fastfacts/display.asp?id=64, [February 2016].

information from schools. Future work should explore the mechanisms by which school financial incentives lead to differential rates of ADHD to mitigate this pattern of medically inappropriate diagnosis.

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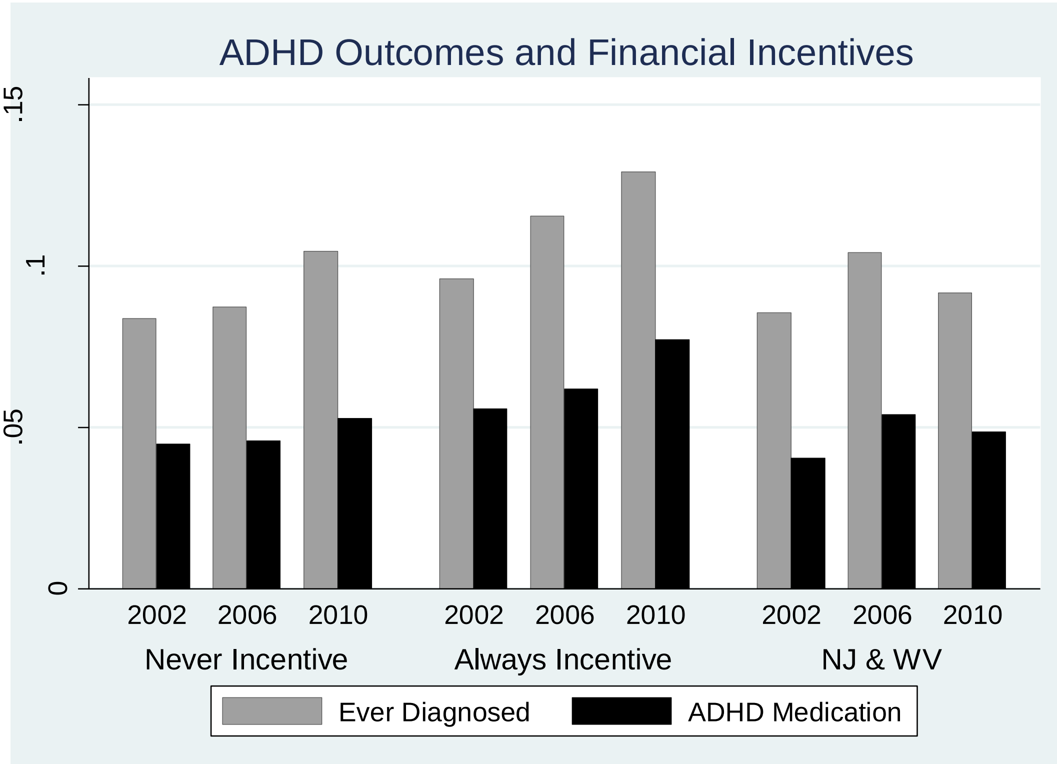


Figure 1: ADHD Outcomes and Financial Incentives

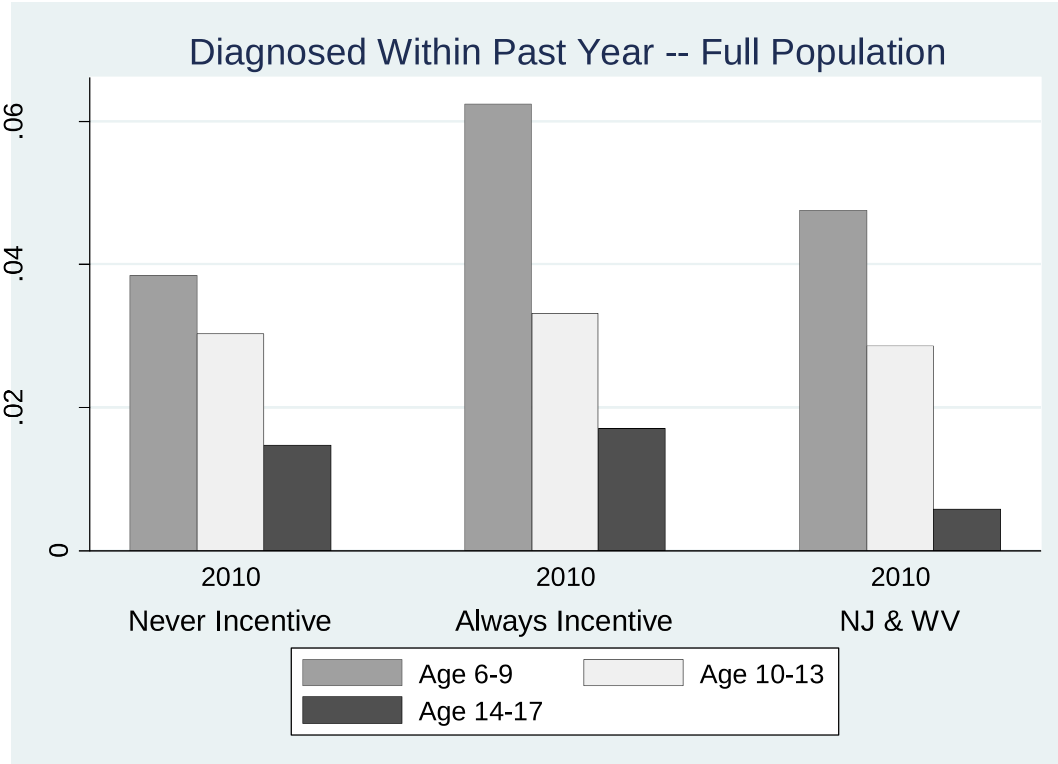


Figure 2: Age of Diagnosis and Financial Incentives

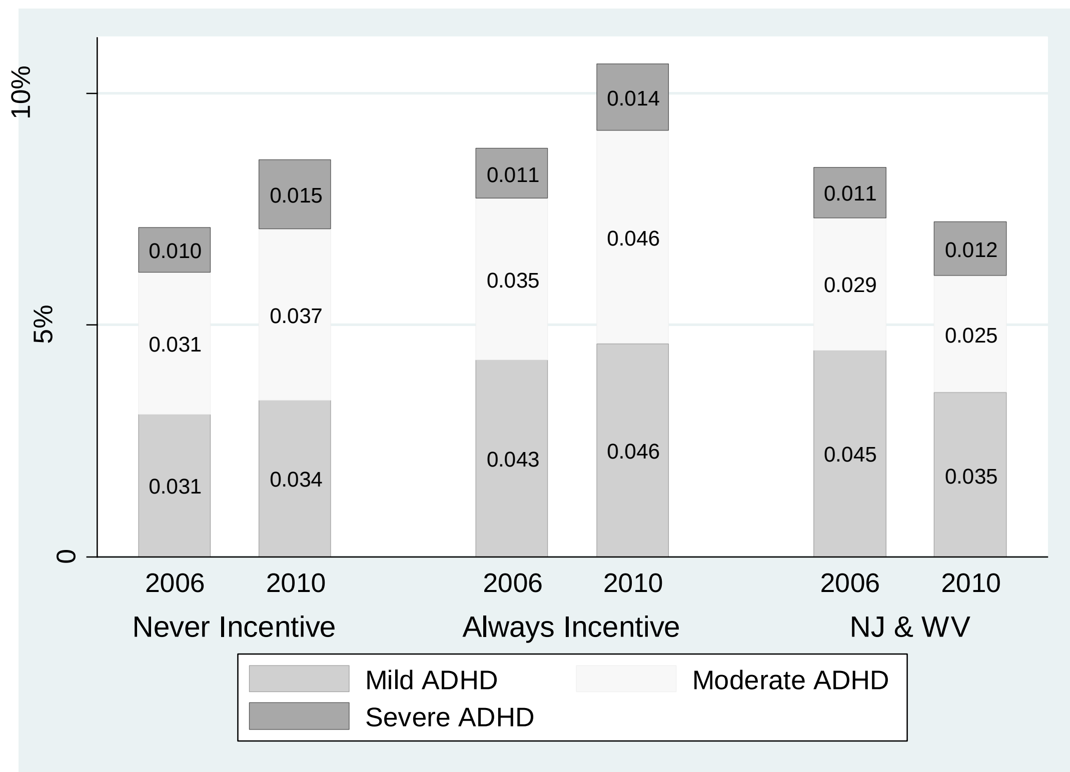


Figure 3: ADHD Severity and Incentives

Table 1: Sample Means

	Full Sample	2003	2007	2011-2012
	(1)	(2)	(3)	(4)
Some Incentive for ADHD Identification	70.6%	72.0%	72.0%	67.9%
Ever Received ADHD Diagnosis	10.7%	9.2%	10.7%	12.1%
Currently Taking Medication for ADHD	6.0%	5.2%	5.7%	6.9%
Demographics				
Male	51.1%	51.0%	51.0%	51.1%
Age	11.6	11.6	11.6	11.6
Non-Hispanic White	61.4%	68.0%	62.6%	54.3%
Non-Hispanic Black	15.7%	16.2%	16.6%	14.4%
Hispanic	14.3%	8.5%	11.9%	21.8%
Other Race	8.6%	7.3%	8.9%	9.6%
Public Health Insurance	27.0%	23.0%	24.4%	33.0%
Private Health Insurance	64.6%	68.2%	66.3%	59.8%
Uninsured	7.2%	7.8%	8.2%	5.8%
DK/Refused Health Insurance Status	0.8%	1.0%	0.0%	1.3%
Family Income <133% FPL	22.0%	19.6%	19.1%	26.9%
Family Income 133%-400% FPL	42.4%	45.5%	43.4%	38.7%
Family Income >400% FPL	27.8%	26.7%	30.2%	26.7%
Family Income Missing/DK	7.7%	8.1%	7.4%	7.6%
Number of Observations	182,706	62,501	58,360	61,845
Implied (weighted) population	133,955,351	43,348,938	43,514,787	47,091,626

Notes: The data are pooled samples of the 2003, 2007, and 2011/2012 National Survey of Children's Health (NSCH) and include all children ages 6 -17 with non-missing values for all variables except where indicated. Hawaii is excluded.

Table 2: ADHD Diagnosis and Treatment by State Special Education Funding Mechanisms

				2003	2007	2011-12
No Financial Incentives All Years:						
AL, AR, CA, CT, ID, IL, MA, MT, ND, PA, RI, SD, UT	Observations:	47,365	Ever Diagnosed	8.4%	8.7%	10.5%
	Population:	37,878K	Medication	4.5%	4.6%	5.3%
Financial Incentives All Years:						
AK, AZ, CO, DE, DC, FL, GA, IN, IA, KS, KY, LA, ME, MD, MI, MN, MS, MO, NE, NV, NH, NM, NY, NC, OH, OK, OR, SC, TN, TX, VT, VA, WA, WI, WY	Observations:	128,037	Ever Diagnosed	9.6%	11.5%	12.9%
	Population:	91,471K	Medication	5.6%	6.2%	7.7%
States Making a Change:						
NJ	Observations:	3,594		Incentive	Incentive	No Incentive (2008)
	Population:	3,840K	Ever Diagnosed	8.1%	9.6%	8.4%
			Medication	3.6%	4.7%	4.2%
WV	Observations:	3,710		Incentive	Incentive	No Incentive (2008)
	Population:	766K	Ever Diagnosed	10.7%	14.1%	13.4%
			Medication	6.2%	8.7%	8.5%

Notes: Data are from the NSCH, see Table 1. The classifications are based on the author's interpretation of state laws as they would apply to a marginal student with ADHD. The Appendix provides a more detailed description of the funding mechanisms and the data sources. The sample excludes the state of Hawaii.

Table 3: ADHD Outcomes and Financial Incentives

	ADHD Ever	Medication for ADHD
	(1)	(2)
Financial Incentive	**0.016**	**0.013**
	(0.005)**	**(0.004)****
Male	0.086	0.051
	(0.004)**	(0.002)**
Age	0.029	0.026
	(0.003)**	(0.002)**
Age^2	-0.001	-0.001
	(0.000)**	(0.000)**
Non-Hispanic Black	-0.023	-0.022
	(0.005)**	(0.003)**
Hispanic	-0.065	-0.049
	(0.008)**	(0.004)**
Other Race/Ethnicity	-0.032	-0.027
	(0.011)**	(0.006)**
Family Income <133% FPL	0.040	0.026
	(0.009)**	(0.006)**
Family Income >400% FPL	-0.017	-0.005
	(0.005)**	(0.002)*
Family Income Miss/DK	-0.022	-0.013
	(0.006)**	(0.004)**
Year 2007	0.019	0.008
	(0.004)**	(0.002)**
Year 2011	0.036	0.023
	(0.003)**	(0.002)**
Constant	-0.141	-0.119
	(0.015)**	(0.010)**
Observations	182,706	182,706
Mean Dep. Var.	0.107	0.060

Notes: Data are from the NSCH, see Table 1. The dependent variable is indicated in the column headings. Coefficients are estimated with a linear probability model, with robust standard errors clustered by state reported in parentheses. ** p<0.01, * p<0.05.

Table 4: State Fixed Effects

	ADHD Ever	Medication for ADHD
	(1)	(2)
Financial Incentive	**0.026**	**0.013**
	(0.003)**	**(0.003)****
Male	0.086	0.051
	(0.004)**	(0.002)**
Age	0.029	0.026
	(0.003)**	(0.002)**
Age^2	-0.001	-0.001
	(0.000)**	(0.000)**
Non-Hispanic Black	-0.028	-0.025
	(0.006)**	(0.003)**
Hispanic	-0.060	-0.046
	(0.009)**	(0.006)**
Other Race/Ethnicity	-0.028	-0.023
	(0.011)*	(0.005)**
Family Income <133% FPL	0.038	0.024
	(0.009)**	(0.005)**
Family Income >400% FPL	-0.017	-0.005
	(0.005)**	(0.002)*
Family Income Miss/DK	-0.023	-0.013
	(0.005)**	(0.004)**
Year 2007	0.018	0.007
	(0.004)**	(0.002)**
Year 2011	0.036	0.022
	(0.003)**	(0.002)**
State Fixed Effects	X	X
Observations	182,706	182,706
Mean Dep. Var.	0.107	0.060

Notes: Data are from the NSCH, see Table 1. Specifications are identical to Table 3 except include state fixed effects. The dependent variable is indicated in the column headings. Coefficients are estimated with a linear probability model, with robust standard errors clustered by state reported in parentheses. ** $p<0.01$, * $p<0.05$.

Table 5: Synthetic Control Methods

Panel A: New Jersey

	New Jersey (1)	Always Incentive States (2)	Synthetic New Jersey (3)
ADHD Ever			
2003	0.081	0.096	0.081
2007	0.096	0.115	0.096
2011-12	0.084	0.129	0.103
ADHD Medication			
	New Jersey (1)	Always Incentive States (2)	Synthetic New Jersey (3)
2003	0.036	0.056	0.036
2007	0.047	0.062	0.047
2011-12	0.042	0.077	0.040

Panel B: West Virginia

	West Virginia (1)	Always Incentive States (2)	Synthetic West Virginia (3)
ADHD Ever			
2003	0.107	0.096	0.107
2007	0.141	0.115	0.141
2011-12	0.134	0.129	0.152
ADHD Medication			
	West Virginia (1)	Always Incentive States (2)	Synthetic West Virginia (3)
2003	0.062	0.056	0.062
2007	0.087	0.062	0.087
2011-12	0.085	0.077	0.092

Notes: Data are collapsed to the state level using individual-specific population weights. Column (1) presents the mean for the treated states, as indicated. Column (2) is the mean of the group of incentive states weighted by population. Column (3) applies state-specific synthetic control group weights. Weights used in Column (3) are presented in Appendix Table C1.

Table 6: Other State-Level Policies and Population Characteristics

	Mean/ Percent	ADHD Ever	Medication for ADHD
		(1)	(2)
Financial Incentive	70.5%	0.012	0.010
		(0.005)*	(0.004)*
School Funding:			
Student Population (1M)	2.2	-0.005	-0.003
		(0.002)*	(0.001)
Percent of Revenue from Local Sources	42.8%	-0.0003	-0.0002
		(0.0003)	(0.0002)
Total Federal Revenue Per Student (1K)	$1.1	0.003	0.004
		(0.010)	(0.007)
Percent Expenditure on Instruction	60.9%	-0.0001	0.0003
		(0.001)	(0.0005)
Total Expenditure Per Pupil (1K)	$9.5	-0.002	-0.003
		(0.001)	(0.001)*
Health Care Market:			
State Medicare Spending/Enrollee (1K)	$17.3	0.004	0.004
		(0.001)**	(0.001)**
State Medicaid Spending/Enrollee (1K)	$12.8	-0.001	-0.00002
		(0.001)	(0.001)
Medicaid Eligibility Threshold	135%	0.0004	0.0004
(Percent of FPL/100)		(0.046)	(0.004)
Mental Health Coverage Mandates:			
Parity	19.7%	0.006	0.0003
		(0.006)	(0.004)
Mandatory Minimum Benefit	34.7%	0.0004	-0.0005
		(0.005)	(0.003)
Mandated Offering	14.2%	0.002	-0.007
		(0.006)	(0.004)
Observations	179,434	179,434	179,434
Mean Dependent Variable		0.107	0.060

Notes: Data and specifications are identical to Table 3 but include the reported additional variables and exclude children living in the District of Columbia. Coefficients are estimated with a linear probability model, with robust standard errors clustered by state reported in parentheses.
** p<0.01, * p<0.05.

Table 7: Other Diseases and Disabilities

	ADHD	Hearing/ Vision	Depression/ Anxiety	Diabetes	Asthma
	(1)	(2)	(3)	(4)	(5)
Financial Incentive	0.016	0.001	0.004	-0.0004	-0.008
	(0.005)**	(0.002)	(0.005)	(0.001)	(0.006)
Male	0.086	0.012	0.013	-0.0005	0.039
	(0.004)**	(0.002)**	(0.002)**	(0.001)	(0.003)**
Age	0.029	0.003	0.007	0.001	0.010
	(0.003)**	(0.001)*	(0.002)**	(0.001)	(0.004)**
Age^2	-0.001	0.000	0.00002	0.00002	0.000
	(0.000)**	(0.000)*	(0.0001)	(0.00003)	(0.000)*
Non-Hispanic Black	-0.023	-0.016	-0.037	-0.001	0.066
	(0.005)**	(0.003)**	(0.005)**	(0.001)	(0.006)**
Hispanic	-0.065	-0.006	-0.033	-0.002	-0.006
	(0.008)**	(0.004)	(0.005)**	(0.001)**	(0.008)
Other Race/Ethnicity	-0.032	-0.002	-0.015	-0.003	0.023
	(0.011)**	(0.003)	(0.009)	(0.001)*	(0.007)**
Family Income <133% FPL	0.040	0.013	0.043	-0.0005	0.027
	(0.009)**	(0.004)**	(0.005)**	(0.001)	(0.008)**
Family Income >400% FPL	-0.017	-0.008	-0.011	-0.003	-0.011
	(0.005)**	(0.002)**	(0.002)**	(0.001)*	(0.004)**
Family Income Miss/DK	-0.022	-0.003	-0.014	-0.0002	-0.022
	(0.006)**	(0.005)	(0.004)**	(0.001)	(0.006)**
Year 2007	0.019	0.019	0.024	0.003	0.015
	(0.004)**	(0.002)**	(0.003)**	(0.001)**	(0.007)*
Year 2011	0.036	0.025	0.031	0.002	0.028
	(0.003)**	(0.002)**	(0.003)**	(0.001)**	(0.005)**
Constant	-0.141	0.006	-0.036	-0.003	0.049
	(0.015)**	(0.007)	(0.011)**	(0.003)	(0.021)*
Observations	182,706	182,706	182,706	182,706	182,706
Mean Dep. Var.	0. 107	0.045	0.072	0.006	0.160

Notes: Sample and specifications are parallel to those in Table 3, Column (1). The dependent variable is ever having been diagnosed with the disease indicated in the column headings. Coefficients are estimated with a linear probability model, with robust standard errors clustered by state reported in parentheses. ** p<0.01, * p<0.05.

Table 8: Sample Heterogeneity

Panel	Interaction Terms	ADHD Ever Mean: 0.107 N=182,706 (1)	Medication for ADHD Mean: 0.060 N=182,706 (2)
A. Baseline	Financial Incentive	0.016	0.013
		(0.005)**	(0.004)**
B. Gender	Financial Incentive	0.009	0.009
(Female)		(0.005)	(0.003)**
	* Male	0.008	0.007
		(0.010)	(0.005)
C. Age	Financial Incentive	0.015	0.016
(Age 6-9)		(0.006)*	(0.005)**
	* Age10-13	-0.009	-0.008
		(0.008)	(0.006)
	* Age 14-17	0.010	-0.001
		(0.006)	(0.004)
D. Race/Ethnicity	Financial Incentive	0.014	0.010
(Non-Hispanic White)		(0.006)*	(0.005)*
	* Non-Hispanic Black	-0.009	0.003
		(0.010)	(0.006)
	* Hispanic	-0.003	0.006
		(0.015)	(0.010)
	* Other Race/Ethnicity	0.036	0.017
		(0.018)*	(0.010)
F. Family Income	Financial Incentive	0.021	0.013
(133%-400% FPL)		(0.005)**	(0.005)**
	* <133% FPL	-0.0001	0.008
		(0.021)	(0.010)
	* >400% FPL	-0.018	-0.005
		(0.009)	(0.005)
	* Missing/DK	0.002	-0.001
		(0.011)	(0.007)
G. Probit Model (Average Marginal Effects)		0.016	0.015
		(0.005)**	(0.005)**
H. Collapsed to State-Level N=150		Mean 0.110	Mean 0.061
		0.005	0.005
		(0.005)	(0.004)

Notes: Each panel presents estimates from separate regressions each ADHD outcome: ever diagnosed (Col. 1), currently diagnosed (Col. 2), and taking medication for ADHD (Col. 3). The estimated coefficients reported are the main effect of the financial incentive on the omitted group (indicated in parentheses after the panel heading) and then the estimated coefficients on the interaction terms between the financial incentive and the group as indicated by row. All specifications include full suite of covariates presented in Table 3 (except where collinear). Coefficients are estimated with a linear probability model, with robust standard errors clustered by state reported in parentheses, except in Panel G, as indicated. ** p<0.01, * p<0.05.

For Online Publication

Appendix A: Detail on State-Level Funding Mechanisms

In this appendix, we first provide a definition of state-level funding mechanism categories. Then, we present a detailed description of each state-level policy and its classification. While we have imposed broad classifications for this study, it should be noted that each state has its own unique special education funding mechanism. Many of the terms used have different meanings across states, such as the ubiquitous term 'block grant'. In addition, many states use a combination of funding strategies. We classify states that have an incentive component to be 'financial incentive' even when a portion of the formula is a form of block grant or census-based.

A further complication is that some states apply different funding mechanisms based on the wealth-level of the population served, such that poorer communities receive relatively higher special education funds. In addition, some states place a cap on the total number of students that can be used in the funding formula, broadly speaking. Both of these additional characteristics of funding could reduce the identification incentives on average. The 'redistributive' special education funding policies could, on the other hand, lead to higher rates of identification amongst the poorer school districts. Table A.1 describes each state's policy in detail and Table A.2 provides a summary. Appendix Table A.3 presents the main results using a finer delineation of state policies.

AI. Financial Incentives: Amount based on identification of children as requiring services

Funding that is based on total enrollment in special education services is generally referred to as 'weighted', 'flat grant', or 'resource-based'. A school district will provide a count of students identified as requiring special education services. Then the state will provide funds that are a function of this total count of students requiring services or a count of the special education units providing the services. States vary in the extent to which actual or anticipated costs per student are reimbursed, with some covering all costs while others only contributing a portion.

Single or Multiple Rate Funds

One method of funding special education services is for the school district to provide a count of students requiring special services or an accounting of special education "units." The state will provide a pre-determined amount for each student or unit, which may vary from year-to-year as budgets permit. States may have different levels of funding, which we label 'multiple rates', depending on the severity of the disability or the intensiveness of services provided within the unit. For example, in Indiana in 2010 per pupil funding for mild/moderate disabilities was $2,265 and for severe disabilities was $8,350.

Single Weight or Multiple Weights

The modal method for funding special education is to adjust the average daily membership or average daily attendance to account for the higher costs of students requiring special services. Then funding is based upon this 'adjusted' average daily membership or average daily attendance. This can be combined with a weighting scheme that allows for more severe disabilities to be given higher weights when calculating a total enrollment number. In some cases, the level of funding is determined by state budgets so the amount of funding given per pupil might vary from year to year. In other states, there is a pre-specified multiplier.

Single weights imply that the same amount of additional funding is given regardless of the disability category. Generally, single weight systems will provide the largest incentive for the identification of children with the least costly (to the district) disabilities. States using multiple weight formulas will apply a higher weight to more expensive/severe disabilities. According to the 1997 Amendments to the IDEA, ADHD is grouped within the category "Other Health Impairment."

Resource-based

Under resource-based financing, states reimburse school districts for the resources used to provide special education services. On the one hand, states are only reimbursed for the resources that they actually use. On the other hand, special education identification can be used to help justify expenses that the school district chooses to incur. In the case of ADHD, students may be identified in order to provide some justification for hiring additional staff members. This is similar to the Multiple Rate mechanism except here any allowed expense can be reimbursed, rather than having a pre-specified reimbursement rate.

Percentage

In some states, only a percentage of the costs of providing special education services are reimbursed. In practice, this is similar to resource-based in the sense that the district spends resources and then receives some reimbursement. In our data, the reimbursed varies widely, with 27.10% in Wisconsin and 28.6138% in Michigan compared to 55% in Nebraska. Many of the states with percentage-based reimbursement vary the percentage yearly based on available funds. We predict that the incentive in these states will be diminished as districts must now pay some portion of the demonstrated expenses. However, the incentive for identifying students as having lower-cost to serve disabilities might still be strong as a means to justify expenditures and provide additional revenue for services.

AII. No Incentive: Special education funding is not based on identification

Census and No Separate Funding

School districts in states categorized as having 'no incentive' will not receive any additional funding for having a student identified as requiring special services. The distinction between census-based and having no separate funding seems to be related to accounting. Most states classified as census-based specifically allocate funds based on average daily membership that are supposed to be used to provide special education services. States classified in the latter category, on the other hand, expect that school districts and schools pay for special education services out of the general funding provided by the state.

In some cases, there are exceptions for severe and high cost disabilities, making the funding somewhat akin to multiple weights or resource-based. Even in this scenario, school districts would not face an incentive to further identify children with ADHD or other disabilities requiring only low-cost services.

Appendix Table A.1: Detailed Description of State Laws

State	Description
AL	1995+: Census-based
AK	1998+: Adjusted ADM is a combination of Block Grant and Single Weight: (1) Block Grant: 1.2 times a base year amount (2) Single Weight: multiplier (5 in 2008, 13 in 2012) times the count of students requiring intensive services. All students with an IEP receiving services are given the same weight.
AZ	Multiple Weights: Base weight is 1.000 grades K-8 and 1.163 grades 9-12 - Group A (includes ADHD) weight is 0.158 grades K-8; 0.105 grades 9-12. Base weights are larger for districts with <600 students.
AR	1996+: No separate funding: Only catastrophic aid for severe and high cost disabilities; instructional materials support for non-severe disabilities, currently $250/pupil.
CA	1997+: Census-based: Funding based on ADA for all districts within each Special Education Local Plan Area (SELPA)
CO	Before 2007: Percentage (80% expenses reimbursed); 2007-2010: Multiple Weights: Tier A funding $1,250 per identified student
CT	1996+: No separate funding: Education Cost Sharing (ECS) aid calculated based on all students weighted for poverty, limited English proficiency, and town wealth. The Special Education Regular Reimbursement grant covers costs of special education in excess of 5 times the prior year's average cost per pupil for eligible students; however, students with ADHD not likely to be covered by this provision.
DE	Prior to 2004: Resource-based, found to be non-ADA compliant 2004-2009: Phase-in of new formula (in 2004 2 districts piloted, by 2008 12 out of 19 had new formula) 2010 all districts had the new formula. New formula is Percentage-based: includes partial unit funding. For ADHD one unit is for 8.4 students; each unit is funded by a fixed percent determined by budget availability.
DC	Multiple Weights: Weight formula updated every few years. 2008-2013 base weight 0.17 + Level 1 weight 0.58.
FL	2001+: Essentially a multiple weight formula with two separate components: (1) Weights for intensive disability categories (the category including ADHD has no extra weight) when calculating funding based on ADM. (2) ADHD and other non-intensive disability categories (and gifted/talented) are funded by the *Exceptional Student Education Guaranteed Funding Amount*. Year-to-year increases in the allocation are based on projected growth in the district's total enrollment in all programs in comparison to growth in ESE enrollment. Funds from this latter source are a function of the number of children identified as requiring non-intensive extra services.
GA	Multiple Weights, ADHD classified as Category III disability: in 2002 is 2.5162 and 2010 is 2.5939. Base allocation amount considers district wealth.
HI[1]	-2006: No Separate Funding: appropriation by legislature based on demonstrated need by school; 2006+: Weight based on service levels (intermittent, targeted, sustained, intensive).

[1] Hawaii has been classified as no separate funding by Parrish (2003) and Ahearn (2010), because special education funding is rolled into general education funding. However, weights are attached while

State	Description
ID	Census: 6% of elementary students and 5.5% of secondary students of fall enrollment counted as eligible special education students. An exceptional child support unit is provided for each 14.5 eligible students.
IL	1995+: Census-based (2004-2007: regular funding plus 17.5% of foundation amount for the year for special education); 2008+: Census-based with two components: (1) 85% of the funds are distributed based on each district's best 3 months average daily attendance from the most recent General State Aid claim (2) 15% funds allocated to school districts based upon the district's low income eligible pupil count used in the calculation of general State aid for the same fiscal year.
IN	1996+: Multiple Rates: Funds for mild/moderate disabilities per child identified. In 2010, per pupil funding under mild/moderate disability category was $2265 and under severe disability category was $8350.
IA	Multiple Weights: 1.68 for "special adaptations to regular classroom".
KS	Percentage: Reimbursement based on full time equivalent (FTE) units needed to provide special education services. The legislature makes an annual appropriation for special education after re-imbursement of student transportation and staff travel. Thus, percentage for reimbursement of costs varies from year to year.
KY	Multiple Weights: ADHD is in moderate incidence category, so has relatively higher weight, 1.17
LA	1995+: Single Weight: 150% of a base amount that varies by budget availability each year.
ME	1997-2004: Percentage: Subsidy to cover costs based on expenditures from the prior two years adjusted for inflation 2004+: Single Weight: Graduated formula includes a weight of 1.27 up to 15% of enrollment; above 15% the weight is 0.38.
MD	Tier 1: Census-based: Funds based on the 1981 total student population. The formula is designed to equalize the state contribution based on property wealth and to apply a cost index bringing counties up to the statewide median per pupil expenditure Tier 2: Single Weight: Annual amount decided by the legislature to be distributed by (1) enrollment data representing the total numbers of children with disabilities, ages 0–21, served; and (2) an equalization component which consists of a ratio of county wealth per pupil to the average state wealth per pupil.
MA	Census-based: funds are allocated for special education at 3.5 percent. This figure is based on an assumption of 14% of the full student census receiving special education services in-district for one-quarter of the school day (14 x .25 = 3.5)
MI	1997+: Percentage reimbursement 28.6138% of total approved instructional costs.
MN	Percentage-based: 68% of special education based salaries of teachers, instructional aides, and other staff providing direct services to students; 47% of supplies and materials used for special education, up to $47 per student and 47% of equipment, with no cap
MS	Resource-based: Special education aid based on approved teacher units. Funding for an approved special education unit is based on the teacher's salary, fixed charges, and support services.

calculating funding by severity of disability. We do not include HI in our analysis because it is one large school district, so is not directly comparable to the incentives in other states.

State	Description
MO	-1998: Single rate per approved class of children and per instructional resource. (In 1994-95, single rate of $3,670 per teacher aide and $14,050 for each approved class of children). 1999-2005 Exceptional Pupil Aid consists of: 1) Single Rate per approved FTE of certified special education teacher, ancillary staff member or instructional aide 2) Census-based amount per eligible pupil (equivalent to an FTE student) enrolled in public school or who is a resident student enrolled in a private/parochial schools, whether the student is disabled or not. 2006+: Single Weight: A threshold is determined yearly to identify high concentration districts. Districts with identified special education students higher than threshold percentage receive additional weight (0.75) only for students above the threshold. The threshold is set as the percentage of special education students in high performing schools and is generally around 14%.
MT	Census-based: Instructional Block Grant (IBG) and Related Services Block Grant (RSBG) and Reimbursement (40%) for disproportionate costs.
NE	Percentage: Allowable excess costs funded on a percentage basis. Estimated reimbursement percentage for 2014 is 55%.
NV	Resource-based: Reimburse all approved costs for each unit servicing students with disabilities.
NH	1999-2008: Multiple Weights: weight of 1.57 for in-district placement with redistribution based on an equalization formula consisting of property wealth, the personal income wealth, and the tax effort of a school district. 2009+ Single Rate: Differentiated aid for each student in special education from July 1, 2009 ($1,856 for school year 2009-10 and $1,881.98 for school year 2013-2014)
NJ	1996-2008: Multiple Weights: Tier 1 state aid is linked to the number of special education students in a district, additional Tier 3 Aid for ADHD 2008+: Census-based: Multiply the district's resident student population by 14.69% to determine the number of special education students to fund. This funded count is then multiplied by the special education per pupil funding amount to determine the total special education funding allotted to the district.
NM	Multiple Weight (+ Resource-based): Pupil units for special education are based on the amount of special education services and revenue is distributed based on the product of the unit value and the cost differential factor (Minimum Services: 0.7 units per student)
NY	-2006: Multiple Weights: 1.80 for ADHD 2007+: Single Weight: 1.41for any disability and 0.5 weight for students in first year of declassification
NC	Single Rate: Funds per child with disability, level is determined by available funds. For FY 2013-14, $3,743 per funded child count, where child count is comprised of the lesser of the Dec. 1 handicapped child count or 12.5% of the allotted ADM.
ND	1991-1994: Resource-based: Funds distributed for special education personnel based on three factors: the units of services provided by the district, the district's special education program costs, and the district's special education program needs 1995+ Census-based Special education weight based on ADM, not number of students identified. Reimbursement for top 1% / extraordinarily high cost cases only.
OH	1997+: Multiple Weights: Additional 0.3691 in FY 2009 for learning disabilities
OK	Multiple Weights: 1.2 for other health impairments (includes ADHD) in counting ADM.
OR	Single Weight: Initial weight is 2, cap of 11%, but partial weight above that ranges from 1.12-1.9
PA	1993+: Census-based: Amount for mild disability * 15% of ADA

State	Description
RI	1997+: No separate funding for special education
SC	Multiple Weights: Weight of 1.74, but base amount differs considerably by year.
SD	1997+: Census-based: Specific dollar amount ($4525 for school fiscal year beginning July 2012 and increased by index factor or 3% whichever is less for following years) for 8.9% of ADM
TN	Resource-based: Average instructional salary for each school system is multiplied by the number of special education staff positions to determine total special education support
TX	Multiple Weights: Weight is based on program, not on disability; lowest weight for mainstream program of 1.1. Special education allotment= adjusted basic allotment* number of FTE in special education program * program weight. The state share is the amount of allotment in excess of the local fund assignment (LFA). LFA is the amount of tax collections generated by assessing the district's compressed tax rate or a tax rate of $1.00, whichever is lower, for each $100 of property valuation, using the preceding school year's property values. Thus, districts with higher property values receive a smaller state share in special education allotment.
UT	Block Grant: Allotment based on allowed growth factor relative to base year. Allowed growth rate cannot exceed ADM growth rate.
VT	Percentage-based: Special education services funded in 3 tiers: (1) Census –based: 60% of statewide average salary for 9.75 FTE special education teaching positions per 1,000 ADM and average special education administrator salary (up to 2.0 FTE administrators for supervisory districts or supervisory unions with more than 1500 ADM) (2) Catastrophic case reimbursement of 90% of funds in excess of $50,000 (3) Percentage-based: Reimbursement rate is a percentage of special education expenditures that is calculated to achieve a 60 percent share of funding from the state across all tiers.
VA	Resource-based: Projected number of personnel based on maximum allowable class size for each disability category to the number of children served as reported on the December special education child count (maximum allowable class size for Other Health Impairment category is 10 with paraprofessional 100% of the time and 8 without paraprofessional 100% of the time).
WA	1995+: Single Weight: Weight of 0.9309 for each special education student.
WV	-2007: Single Weight: Weight of 1.0 (district receives twice the typical funding for each special education student). 2008+: No separate formula: New formula was phased-in over 5 years, with districts receiving a portion of the differential between the two levels of funding.
WI	Percentage-based: Approved costs reimbursed. Prorated reimbursement rate steadily declined to 27.10% for 2013-14.
WY	1997+: Resource-based: 100% reimbursement for personnel costs of providing full-time special education programs.

Appendix Table A.2: Categorizations of State Special Education Funding Mechanisms

State	Type of Formula 2002	Type of Formula 2006	Type of Formula 2010	State	Type of Formula 2002	Type of Formula 2006	Type of Formula 2010
AL	Census	Census	Census	MT	Census	Census	Census
AK	Single Weight	Single Weight	Single Weight	NE	Percentage	Percentage	Percentage
AZ	Redistribution	Redistribution	Redistribution	NV	Resource	Resource	Resource
	Multiple Weight	Multiple Weight	Multiple Weight	NH	Redistribution	Redistribution	Single Rate
AR	No Separate	No Separate	No Separate		Multiple Weight	Multiple Weight	
CA	Census	Census	Census	NJ	Multiple Weight	Multiple Weight	Census
CO	Percentage	Percentage	Multiple Weight	NM	Multiple Weight	Multiple Weight	Multiple Weight
CT	No Separate	No Separate	No Separate	NY	Multiple Weight	Multiple Weight	Single Weight
DE	Resource	Percentage	Percentage	NC	Cap Single Rate	Cap Single Rate	Cap Single Rate
DC	Multiple Weight	Multiple Weight	Multiple Weight	ND	Census	Census	Census
FL	Multiple Weight	Multiple Weight	Multiple Weight	OH	Redistribution	Redistribution	Redistribution
GA	Multiple Weight	Multiple Weight	Multiple Weight		Multiple Weight	Multiple Weight	Multiple Weight
~~HI~~	~~No separate~~	~~Multiple Weight~~	~~Multiple Weight~~	OK	Multiple Weight	Multiple Weight	Multiple Weight
ID	Census	Census	Census	OR	Redistribution	Redistribution	Redistribution
IL	Census	Census	Census		Single Weight	Single Weight	Single Weight
IN	Multiple Rate	Multiple Rate	Multiple Rate	PA	Census	Census	Census
IA	Redistribution	Redistribution	Redistribution	RI	No Separate	No Separate	No Separate
	Multiple Weight	Multiple Weight	Multiple Weight	SC	Redistribution	Redistribution	Redistribution
KS	Percentage	Percentage	Percentage		Multiple Weight	Multiple Weight	Multiple Weight
KY	Multiple Weight	Multiple Weight	Multiple Weight	SD	Census	Census	Census
LA	Single Weight	Single Weight	Single Weight	TN	Resource	Resource	Resource
ME	Percentage	Single Weight	Single Weight	TX	Redistribution	Redistribution	Redistribution
MD	Redistribution	Redistribution	Redistribution		Multiple Weight	Multiple Weight	Multiple Weight
	Single Weight	Single Weight	Single Weight	UT	Block Grant	Block Grant	Block Grant
MA	Census	Census	Census	VT	Percentage	Percentage	Percentage
MI	Percentage	Percentage	Percentage	VA	Resource	Resource	Resource
MN	Percentage	Percentage	Percentage	WA	Single Weight	Single Weight	Single Weight
MS	Resource	Resource	Resource	WV	Single Weight	Single Weight	No separate
MO	Single Rate	Single Weight	Single Weight	WI	Percentage	Percentage	Percentage
				WY	Resource	Resource	Resource

Notes: The classifications are based on the author's interpretation of state laws as they would apply to a marginal student with ADHD. A more detailed description of the funding mechanisms is provided in Appendix Table A1.

Appendix Table A3: Finer delineation of state laws

	Percent of Children with Funding Type	ADHD Ever		Medication for ADHD	
		(1)	(2)	(3)	(4)
Financial Incentive:					
Single Weight or Rate	8.9%	0.008	0.021	0.009	0.014
		(0.009)	(0.002)**	(0.007)	(0.001)**
Multiple Weights or Rates	21.1%	0.016	0.029	0.010	0.015
		(0.006)**	(0.002)**	(0.004)*	(0.002)**
Percentage-based	10.5%	0.007	0.036	0.010	0.027
		(0.006)	(0.007)**	(0.004)*	(0.004)**
Resource-based	6.9%	0.019	0.007	0.013	0.013
		(0.007)*	(0.009)	(0.006)*	(0.005)*
Redistribution Single Weight	3.2%	0.022		0.011	0.022
		(0.010)*		(0.008)	(0.010)*
Redistribution Multiple Weights	16.9%	0.020	0.013	0.019	0.019
		(0.005)**	(0.003)**	(0.005)**	(0.003)**
Cap on Funding	3.1%	0.050		0.043	
		(0.004)**		(0.003)**	
No Incentive:					
Block Grant	1.1%	-0.020		-0.017	
		(0.004)**		(0.003)**	
No Separate Funding	2.7%	0.021	0.006	0.015	0.007
		(0.012)	(0.002)*	(0.011)	(0.002)**
Census-Based (Omitted category)	25.7%				
N		182,706	182,706	182,706	182,706

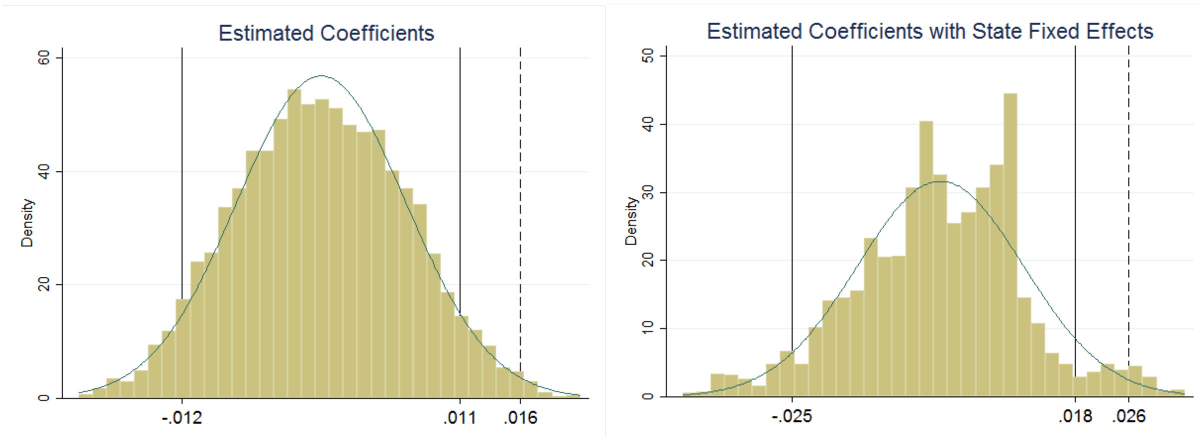
Notes: Specification is identical to Table 3 except the financial incentive variable. Included controls for year, gender, age, race, insurance, and poverty are not reported. The first column reports the mean number of children living under each policy. * significant at 5%; ** significant at 1%.

Appendix B: Permutation Tests for Inference

In difference-in-differences settings where there are only a small number of policy changes, usual methods for calculating standard errors can lead to inconsistent estimates and rejection rates are generally too low (Conley and Taber, 2011; MacKinnon and Webb, 2016). When including state fixed effects, our application faces a similar problem. Following the example in Ebenstein and Stange (2010), based on Fisher's randomization tests (Fisher 1935), this Appendix presents results from a nonparametric permutation test. Here, we have three "groups" of states: never had an incentive (13 states), always had an incentive (35 states), and incentive was removed in 2008 (2 states). Thus, the methods explored in Conley and Taber (2011) and MacKinnon and Webb (2016) are not directly applicable.

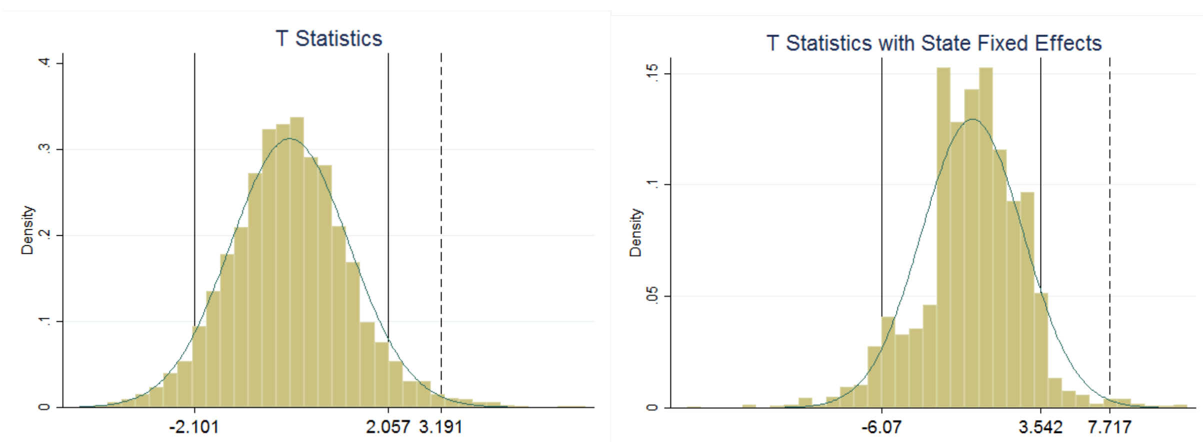
We randomly reassign states without replacement to groups (never incentive, always incentive, incentive removed in 2008) keeping constant the *number of states* in each group. The regressions are estimated at the individual-level and include an individual-specific weight. Thus, the size of the state will be accurately represented but each state will be randomly assigned to a three time period policy regime. Because MacKinnon and Webb (2016) argue that t-statistics have superior properties to estimated coefficients, we include figures of both estimated coefficients and t-statistics. Appendix Figure B.1 illustrates the distribution of estimated coefficients on the financial incentive variable without and with state fixed effects, matching the estimates reported in Table 3 Columns (1) and Table 2, Column (1), respectively. The bars indicate the distribution of estimated coefficients from 5,000 separate regressions where states were randomly assigned without replacement to one of three groups retaining the number of states in each group. A normal distribution is plotted and illustrates that the estimates from these placebo regressions are approximately normally distributed. The solid lines denote the 5th and 95th percentiles of the distribution. The dashed line is the estimated coefficient value from the actual regression. In both cases, we can see clearly that the estimated coefficients are above the 95th percentile of the distribution. We can also see that with state fixed effects the estimates are not converging (as quickly) to a normal distribution, which is precisely the issue addressed in Conley and Taber (2011).

MacKinnon and Webb (2016) show that *t* statistics have better analytic properties than estimated coefficients in permutation tests. In Appendix Figure B.2, we graphically present the *t* statistics from these same placebo regressions. We see that the actual estimated t-statistics, represented by the dashed lines, are well above the 95th percentile of the distribution. We again note that the distributions in the specification with fixed effects are noisier. The results of ad-hoc permutation tests confirm that null can be rejected even when state fixed effects are included.



Notes: These figures correspond to the specifications presented in Table 3 Column (1) and Table 4 Column (1), without and with state fixed effects, respectively.

Appendix Figure B.1: Permutation Tests of Estimated Coefficients from Randomly Reassigning Treatment Status to States



Notes: These figures correspond to the specifications presented in Table 3 Column (1) and Table 4 Column (1), without and with state fixed effects, respectively.

Appendix Figure B.2: Permutation Tests of T-Statistics from Randomly Reassigning Treatment Status to States

Appendix Table C1: Weights for Synthetic Control Groups

	New Jersey		West Virginia	
	ADHD Ever (1)	Medication for ADHD (2)	ADHD Ever (3)	Medication for ADHD (4)
AK	0.022	0	0.007	0.006
AZ	0.036	0	0.005	0.010
CO	0.231	0.880	0.004	0.019
DC	0.031	0	0.005	0.009
DE	0.010	0	0.023	0.022
FL	0.013	0	0.018	0.014
GA	0.015	0	0.014	0.013
IA	0.017	0	0.012	0.016
IN	0.015	0	0.012	0.022
KS	0.017	0	0.011	0.015
KY	0.010	0	0.032	0.100
LA	0.008	0	0.064	0.023
MD	0.012	0	0.021	0.017
ME	0.019	0	0.009	0.011
MI	0.014	0	0.016	0.013
MN	0.027	0	0.006	0.011
MO	0.019	0	0.009	0.027
MS	0.012	0	0.165	0.015
NC	0.007	0	0.348	0.444
NE	0.031	0	0.006	0.012
NH	0.017	0	0.010	0.012
NM	0.039	0	0.005	0.008
NV	0.167	0.116	0.004	0.004
NY	0.027	0	0.006	0.009
OH	0.013	0	0.016	0.015
OK	0.017	0	0.011	0.018
OR	0.020	0	0.008	0.012
SC	0.009	0	0.056	0.018
TN	0.012	0	0.030	0.018
TX	0.015	0	0.014	0.009
VA	0.013	0	0.021	0.011
VT	0.027	0	0.006	0.011
WA	0.019	0	0.009	0.010
WI	0.017	0	0.011	0.013
WY	0.023	0	0.007	0.013

Notes: Synthetic weights are created by minimizing MSPE over time periods 2002 and 2006 using the predictors male, age (quadratic), race, poverty, population size, and ever diagnosed and current medication.