Peer Effects, Institutions and Human Capital Accumulation: The Externalities of ADD

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Abstract

Recent work shows that peers affect student achievement, but the mechanisms are not well understood. I show that peer behavior is an important mechanism, perhaps more so than ability, by exploiting exogenous timing in diagnosis/treatment of ADD among peers that improves peer behavior while holding peer achievement constant. Improvements in peer behavior increase student achievement. Moreover, resources mitigate the negative effects of peer behavior. These findings imply that the optimal response in the presence of peer effects is not necessarily to reorganize classrooms. Rather, existing institutions can modify peer effects by improving behavior and/or mitigating the impact of poor behavior.

I. Introduction

Research on the determinants of human capital accumulation has focused increasingly on the role of peers, but estimating peer effects is hindered by selective sorting across schools and potential omitted variable bias. Recent work has employed novel identification strategies based, in part, on quasi-randomization of high achieving peers to estimate peer effects. But because peer achievement is a function of multiple factors, the estimates do not allow one to draw any conclusions about the mechanism(s) by which peer achievement affects student achievement. High achieving peers are on average more able and better behaved. Knowing whether ability, behavior or some combination of the two is responsible for observed peer effects is necessary for the development of an accurate model of education production and has important implications for how we organize schools and classrooms. If ability, which is generally considered fixed or difficult to modify, is solely responsible for observed peer effects, then the appropriate policy response would be to re-organize classrooms. However, if behavior which is more malleable than ability proves to be an important factor, then the optimal response may be to design policies that improve student behavior as they are likely easier to implement than policies that redistribute students based on ability - a poorly measured and often unobserved characteristic.

In this paper I provide strong evidence that peer behavior is an important input in education production, perhaps more so than peer ability. To do so I estimate the impact of having classmates with ADD before and after diagnosis. I show that before students are diagnosed with ADD they display greater externalizing behavior problems and worse self-control. After diagnosis, their behavior improves but their cognitive achievement does not, consistent with a large body of work in the medical literature.[1]

To address issues of selection into peer groups, I include individual fixed effects (which subsume school fixed effects) to control for sorting across schools. To address the potential for any sorting within schools over time (eg, dynamic sorting or tracking) that might be correlated with a diagnosis of ADD, I pursue multiple strategies. First I provide evidence that the timing of diagnosis is uncorrelated with peer characteristics including their past achievement, or observed teacher characteristics. Second, I bypass altogether the issue of selective sorting within schools over time by redefining the peer groups as all students in the grade (not the classroom). Finally, I instrument for the timing of diagnosis using expansions in public health insurance through Medicaid/SCHIP. Medicaid/SCHIP expansions increase the probability of health insurance coverage and lower the cost of diagnosis and treatment of ADD but otherwise should have no effect on classroom composition, teacher quality or student test scores.[2]

There are two advantages to this identification strategy. First, by using a diagnosis of ADD to identify peer effects one can identify the relative importance of peer behavior, holding achievement constant. Second, the policy used to instrument is not an education policy and thus is more arguably exogenous in this context.

There are four main findings. First, children with undiagnosed (and therefore untreated) ADD generate negative externalities in the classroom, lowering the reading and math test scores of their classmates: if 8.5 percent of the class have undiagnosed ADD (the standard deviation in these data), test scores will be between 1 and 2 points, 10-20 percent of a standard deviation, lower. Once diagnosed, students with ADD generate no such negative externalities. This represents a moderate impact given previous findings that a one standard deviation increase in peer test scores increases individual test scores by 35 percent of a standard deviation (Hanushek et al, 2003). Second, once diagnosed, children with ADD see significant improvements in their

[1] Swanson et al (1991) provide evidence that higher than optimal doses prescribed to children when improvements in behavior (rather than cognitive achievement) are used to gauge success can explain this finding. I return to this point later.
[2] I discuss whether the exclusion restriction is met later.

own behavior but no improvement in their achievement, consistent with medical evidence and suggesting that the students with undiagnosed ADD negatively affect peer achievement through their disruptive behavior. Third, these effects are concentrated among boys. This can potentially be explained by the fact that peer groups at early ages are largely gender-specific (Maccoby, 1995) and ADD is a disorder that mostly affects boys. However, it may also be that girls are simply less affected by disruptive behavior in the classroom. Finally, I show that institutions can play an important role in both affecting peer behavior and mitigating the impact of negative peer behavior. Specifically, I find that expansions in public health insurance increase the number of children with health insurance, thereby increasing the probability of diagnosis and reducing problematic behavior. Moreover, I find that resources (most notably class size) can overcome the negative peer effects observed, consistent with the model of peer effects proposed by Lazear (2001).

These findings have a number of important implications. First, they contribute to the existing literature on peer effects in the classroom, shedding light on one potential mechanism through which peer effects operate. While these estimates of the impact of inattentive/impulsive behavior are derived from students with ADD, they likely generalize to other problematic or disruptive behavior in the classroom, suggesting that the total peer effect due to behavior exceeds these estimates. Second, the finding that achievement of girls is less affected by disruptive behavior in the classroom can potentially explain part of the widening gender gap in school achievement. Third, the results suggest that peer effects should be considered within their institutional framework: health and educational resources can affect peer behavior and mitigate the negative effects of peer behavior. As such, policy discussions need not be limited to how best to compose classrooms to maximize peer effects. Rather, policies that also consider the ways in which teacher, school, and community resources (health care in the case of ADD) influence or mitigate peer effects via student behavior may ultimately be easier to implement and just as effective.

Finally, the results of this paper contribute to our understanding of the relationship between health, productivity and growth. Previous work has linked children's physical and mental health with their own human capital accumulation (Grossman and Kaestner, 1997; Currie and Stabile, 2007; Fletcher and Wolf, forthcoming). Other work (Weil, 2007; Shastry and Weil, 2005) have estimated the effect of physical health on income per capita. Results presented here suggest that mental health may also play an important role in explaining growth – not only through its impact on the human capital accumulation of those with a mental disorder, but also through externalities imposed on others.

The rest of the paper is organized as follows: section II contains background information on ADD and the peer effects literature; section III describes the data; section IV presents a model of student achievement that makes explicit what kind of education production function would yield these empirical results and also helps us to interpret the empirical estimates; section V presents estimates of the impact of diagnosis on one's own achievement and behavior. Sections VI and VII contain the fixed effect and instrumental variable estimates of the externalities associated with untreated ADD, respectively; section VIII includes a cost-benefit analysis of treatment; section IX includes two additional robustness checks and section X concludes.

II. Background

A. ADD: Symptoms, Prevalence and Etiology

ADD is characterized by inattention, impulsivity and hyperactivity. For a medical diagnosis of ADD, the symptoms must be more frequent or severe than in other children the same age and at least some of the symptoms must have been present before age 7, according to the <u>Diagnostic and Statistical Manual of Mental Disorders IV</u>. Data from the National Health Interview Survey (NHIS) show that the proportion of children diagnosed with ADD increased from five to six percent over the period 1997-2004. ADD is much more common among boys and rates of diagnosis increase with age until age 11-12 when they plateau. In 2003, prevalence among boys between the ages of four and six was five percent, increasing to 11 percent for those aged 11-12, and remaining steady at 12 percent for those age 13-17.

Children with ADD are characterized by worse behavior and lower cognitive achievement (see Mannuzza and Klein, 2000 for a review; Currie and Stabile, 2007). The negative impact of ADD on behavior is significant. Barkley et al (1990) finds that almost half of students with ADD had been suspended from school. Greene et al (2002) find that students with ADD consume a significantly higher percentage of teacher attention and that teachers report significantly greater stress in their interactions with them.

There is mounting evidence in the medical literature that ADD is biologically determined, with much of the evidence based on brain imaging studies (Swanson et al 2001; Castellanos, 2001; Waldman et al, 1998; Rowe et al, 1998). This is consistent with recent work that suggests that children with ADD display many of the symptoms associated with the disorder in preschool (Campbell and Ewing, 1990) even though most children are not diagnosed with the disorder until later.

B. Impact of Treatment on Behavior and Cognitive Achievement

Of youths diagnosed with ADD, an estimated 78% are prescribed one or more stimulants (Guevara et al, 2002).[3] Medical evidence suggests that diagnosis and treatment of ADD positively affects behavior in 70-80 percent of children but has little impact on cognitive achievement. In a recent review of the literature, Spira and Fischel (2005) conclude that for children with ADD "stimulants may increase on-task behavior, decrease disruptive behavior, and even increase the amount of class work completed, but they do not appear to have a significant effect on the accuracy of that work." Recent work in the economics literature by Currie and Stabile (2007) and Fletcher and Wolf (forthcoming) based on large datasets of children followed over time for many years is consistent with these findings.

Swanson et al (1991) shed light on why treatment has consistently been found to improve behavior but not achievement. In a review of the medical research on the topic, they conclude that when behavioral responses are used to gauge treatment effectiveness in children (as they nearly always are), it often leads to medication dosage which exceeds target levels for improved cognitive performance, a phenomenon they refer to as "cognitive toxicity."[4] I incorporate this concept of cognitive toxicity in the model of ADD treatment and peer effects presented in section IV to explain why we find no effect of treatment on a child's own achievement, but we do find an effect on the achievement of his peers.

C. Peer Effects Literature

Most of the empirical literature on peer effects examines the impact of peer achievement on own achievement. The primary challenge to identifying peer effects lies in overcoming the endogeneity of one's peer group. Specifically, issues of self-selection, omitted variables and simultaneity may bias estimates of peer effects. Selection refers to the fact that students select

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[3] For those not prescribed stimulants, antidepressants, antipsychotics, and clonidine are often prescribed.
[4] In describing this phenomenon, Swanson et al (1991) refer to medical children as "zombie-like."

their peer groups largely through their choice of school. Omitted variables might include unobserved aspects of teacher quality that affect both the student and his peers. Finally, simultaneity refers to the fact that while a student is influenced by his peers, he also influences his peers (Brock and Durlauf, 2001; Manski, 1993; Moffitt, 2001.)

Many papers employ novel techniques to identify the causal impact of peers. Hanushek et al (2003) identify peer effects by estimating the impact of differences in peer characteristics for cohorts of students within the same school. They find that peer achievement does have a significant and positive impact on achievement. Angrist and Lang (2004) study Metco, a desegregation program in Boston which dramatically increased the number of low-performing black students in predominantly white suburban schools, and find little effect. By focusing on a policy of forced desegregation they too overcome issues of self-selection and other omitted variables. Cooley (2006) estimates the impact on high achieving students of a change in policy that raises the bar for promotion for low achieving students.[5]

The above-mentioned natural experiments, however, do not lend themselves to identification of the mechanism(s) by which peers affect student achievement. High achieving peers might matter because they are more able, or because they are less disruptive. The latter would be consistent with the model proposed by Lazear (2001) in which the ability of a student to learn depends on the behavior of his classmates because it reduces effective teaching time or directly interferes with his work. Distinguishing between the potential mechanisms has proven difficult. In a recent empirical paper on peer effects, Hanushek et al (2003) write "In general there has been limited attention given to the mechanism through which peers affect outcomes…Most analyses have focused on the identification of the "reduced form" relationship between outcomes and specific measures of peer group quality, typically ignoring the precise structure of the underlying causal relationship."

Recent empirical work provides some evidence on the role of peer behavior in determining cognitive outcomes. Three of these papers focus on the impact of having more girls in a classroom. Hoxby (2000) exploits variation in gender (racial) composition to estimate the impact

[5] Other work on peer effects include Evans, Oates and Schwab (1992), Betts and Morell (1998), Epple and Romano (1998), Vigdor and Nechyba (2005). Of these, Evans Oates and Schwab (1992) and Vigdor and Nechyba (1998) find that peer effects estimated via OLS are not robust under simultaneous equation estimations for the former or the inclusion of teacher fixed effects for the latter. Gavira and Raphael (2001) look at peer effects in the context of juvenile behavior. Sacerdote (2001) and Zimmerman (2003) find positive peer effects among college students.

of peer gender (race) on achievement. Whitmore (2005) finds that even conditional on peer achievement, more girls in a classroom generates positive effects. Though she does not speculate why – the evidence presented here suggests that this could be because girls are characterized by less disruptive behavior. This is consistent with more recent findings that more girls reduce classroom disruption and improve inter-student and student-teacher relationships (Lavy and Schlosser, 2007).

Three other paper focus specifically on peer behavior. Figlio (2005) uses the presence of a boy with a feminine name to instrument for classroom disruption, arguing that such boys are more prone to fighting but are not characterized by lower cognitive ability. He finds large negative effects on achievement. Lavy, Paserman and Schlosser (2007) find that low-achieving peers negatively affect student achievement, particularly those at the bottom of the distribution, and suggests that this due to the fact that they are more disruptive and negatively affect the ability of teachers to teach.[6] Finally, Neidell and Waldfogel (2008) exploit variation in pre-school attendance to identify the impact of kindergarten peer behavior on cognitive achievement. They find that having only a small number of disruptive children in the classroom can negatively affect the cognitive achievement of others.

In this paper I estimate the relative importance of peer behavior in producing student achievement by exploiting a novel source of identification (described in detail in the next section.) Moreover, I estimate the impact of resources (health insurance and classroom resources) on peer behavior. As a result, the policy implications of this work differ considerably from previous work. While previous work sheds light on the positive impact of removing low performing, male, or disruptive students from the classroom it does not allow one to determine the optimal allocation of these students. In contrast, my findings suggest that either improving the behavior of peers by, for example, increasing access to medical care for diagnosis and treatment of ADD or other mental health disorders (not necessarily removing them from the class), or mitigating the negative effects of peer behavior with an increase in classroom resources can have a positive impact on student achievement.

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[6] In related work, Argys and Rees (2008) exploit exogenous differences in the age of peers due to kindergarten start dates to estimate the impact of relative youth on risky behavior. They find that among girls, having older peers is associated with an increase in risky behavior. They conclude that peer behavior is contagious and that the impact of peer behavior differs by gender.

D. Overview of Identification Strategy

To identify the importance of peer behavior relative to peer cognitive ability I estimate the impact of having classmates with ADD before and after diagnosis on student test scores. I argue and provide evidence that before students are diagnosed with ADD they display greater externalizing behavior problems. After diagnosis, their behavior improves but their cognitive achievement does not. I assume that this is because of a concurrent decline in cognitive ability associated with over-medication ("cognitive toxicity") which is well-documented in the medical literature. Thus, in estimating the impact of changes in peer diagnosis on achievement one can estimate the impact of improvements in peer behavior relative to declines in cognitive ability holding other characteristics (including achievement) constant.

For identification, ideally one would observe the same group of classmates over time and all variation would come from changes brought about by diagnosis of ADD. However, the data do not allow this: classroom composition does not stay constant from Kindergarten through grade five in these data. Rather, there is re-sorting of children among classrooms in a given cohort over time (Rothstein, forthcoming). The inclusion of fixed effects which addresses non-random selection into schools as well as unobserved fixed characteristics of children would not address this.

To address this threat to validity, I pursue three strategies. First, I provide multiple pieces of evidence that the timing of diagnosis appears to be exogenous in this context, which I discuss in greater detail in section VI. As a second strategy, I redefine the share of peers with undiagnosed ADD over all students in one's grade in school. In so doing, I drop altogether the assumption that re-sorting of students across classrooms over time is uncorrelated with the ADD status of one's peers. Implicitly, the source of identifying variation in the grade-level analysis comes from different rates of diagnosis over time across schools and assumes that they are not correlated with growth in test scores for reasons independent of diagnosis of ADD.[7]

As a third and final strategy, I drop the assumption of random timing of diagnosis altogether and instrument for diagnosis using expansions in publicly provided health insurance. Expansions in health insurance coverage reduce the cost of medical diagnosis and treatment but are uncorrelated with peer or teacher characteristics that might independently affect both

[7] To support this empirically, I show that the rate of diagnosis within school is uncorrelated with female test score growth.

diagnosis and treatment. An advantage of this identification strategy is that the policy used to instrument for diagnosis is not an education policy. As such, we may be less concerned that the policy change coincides with other changes affecting students, teachers or schools. Instrumenting for the timing of diagnosis also addresses concerns regarding both mean reversion (Ashenfelter dip) and the potential for non-random timing of diagnosis that could bias the fixed effect estimates. The empirical methods are described in greater detail in sections VI and VII.

Before presenting the empirical results I develop a model of education production. The model serves two purposes. First, it makes explicit what assumptions regarding the form of the education production function and the impact of diagnosis/treatment of ADD on own cognition and behavior yield the prediction that diagnosis does not improve own achievement but does improve peer achievement. Second, it aids in interpretation of the estimates of the impact of diagnosis on peer achievement.

III. A Model of Peer Effects in the Classroom

In this section I present a model of peer effects in the classroom that is consistent with the empirical findings that even though treating a student with ADD will not improve his own achievement it will increase the achievement of his peers. Two main assumptions underlie this model. The first regards the inputs into the production of student achievement. In this model, a student's achievement is a function of his own cognitive ability and his own behavior, (a straightforward assumption). Achievement is also a function of the average cognitive ability and behavior of his classmates (peers). In this model, a student's achievement is not a function of peer achievement, but rather the inputs of peer achievement: peer ability and peer behavior. More able peers positively affect achievement because they require less teacher time (indirect effect) or because students learn from them (direct effect). Better behaved peers positively affect achievement because they are less disruptive, thereby requiring less teacher time for discipline (an indirect effect) and interfering with the learning of their classmates less frequently (a direct effect). Classroom resources do not enter into the education production function here because they are assumed to be uncorrelated with ADD diagnosis (an assumption for which I provide empirical support), and thus are not a factor in the comparative statics. They may, however, serve to mitigate the negative effects of either poor ability or behavior, a point to which I return.

The second assumption regards the impact of diagnosis on a student's own ability, behavior and achievement. This assumption is based on the empirical regularity that treatment of children with ADD improves behavior but does not improve achievement. This has been well documented in the medical literature and the same pattern is also present in the ECLS-K data, as shown in the next section. Moreover, medical researchers have recently proposed an explanation: over-dosage of medication leading to "cognitive toxicity" which is essentially a reduction in cognitive ability (Swanson et al, 1991). Based on this, I assume that diagnosis/treatment of a student with ADD will lower his cognitive ability but improve his behavior and that these two forces work in opposite directions such that on net there is no impact of treatment on achievement.

These two assumptions underlie the model presented below.

The Model

In this model of peer effects in the classroom, a student's achievement (as measured by test scores) is a function of his own cognitive ability, his own behavior and the cognitive ability and behavior of his classmates, summarized as follows:

$$S_i = \alpha + \phi C_i + \theta B_i + \beta \frac{\sum_{j\neq i} C_j}{(n-1)} + \gamma \frac{\sum_{j\neq i} B_j}{(n-1)}$$

Where *i* indexes focal child, *j* indexes his classmates and *n* is the number of students in the class. S_i refers to his own cognitive achievement test scores in either reading or math, C_i refers to his own cognitive ability and B_i to his own behavior. The two last terms in the equation above refer to the average cognitive ability and behavior of his classmates, respectively. According to this model, it is not peer achievement that matters, but rather the two main inputs into peer achievement: peer ability and behavior.

In this example, student *i* is diagnosed with ADD. When diagnosed, his achievement changes as follows:

$$\Delta S_i = \phi \Delta C_i + \theta \Delta B_i$$

We know from a large body of research in the medical sciences (and confirmed in analyses presented here) that after diagnosing and treating of students with ADD, achievement does not change (ΔS_i =0), but that behavior does improve (ΔB_i >0). If so, then

$$\Delta C_i = \frac{-\theta \Delta B_i}{\phi} \qquad (1)$$

and the positive impact of an improvement in behavior on achievement is offset by a decline in cognitive ability (ΔC_i<0), referred to as “cognitive toxicity” resulting from over-medication of children with ADD.

For peers of the student diagnosed with ADD, achievement is characterized by:

$$S_j = \alpha + \phi C_j + \theta B_j + \beta \frac{\sum_{k \neq j} C_k}{(n-1)} + \gamma \frac{\sum_{k \neq j} B_k}{(n-1)}$$

We assume that diagnosing a student with ADD affects only his cognitive ability and behavior - it does not affect the cognitive ability or behavior of his classmates. Thus the change in achievement for peer *j* of diagnosing student *i* can be written as

$$\Delta S_j = \beta \Delta C_i + \gamma \Delta B_i$$

Where ΔC_i and ΔB_i are the changes in cognitive ability and behavior, respectively, of those in the classroom diagnosed and treated for ADD. From equation (1) we can substitute $\frac{-\theta \Delta B_i}{\phi}$ for ΔC_i in the above equation. If we observe a positive impact of diagnosing a student on classmate test scores, $\Delta S_j > 0$, this implies that

$$\beta \frac{-\theta}{\phi} \Delta B_i + \gamma \Delta B_i > 0$$

Which is equivalent to:

$$\Delta B_i (\gamma - \beta \frac{\theta}{\phi}) > 0$$

Since the change in behavior (ΔB_i) is positive, it must be the case that

$$\frac{\gamma}{\theta} > \frac{\beta}{\phi}$$

The interpretation of the above is that the impact of peer behavior on achievement (γ) exceeds the impact of peer cognitive ability (β) relative to the impact of own behavior (θ) and own ability (φ). This helps us to interpret our findings, presented in sections V-VII, that diagnosing students with ADD does not increase their own achievement but does increase peer achievement.

IV. Data

A. Data Description

The data for the empirical analyses come from the restricted use Early Childhood Longitudinal Survey – Kindergarten Cohort (ECLS-K). The ECLS-K cohort consists of a nationally representative group of nearly 20,000 children who entered Kindergarten in the Fall of 1998, drawn from roughly 1000 schools. Data are collected for students in kindergarten, first, third, fifth and eighth grades. Teachers, parents and school administrators are surveyed each year. The data include information on family background, teacher characteristics, classroom composition, as well as behavioral and cognitive assessments. The behavioral assessment consists of teacher scores on an externalizing behavioral problem scale (scale 1-4 with 4 indicating worse behavior). These scores are collected only through grade 5. Assessments of cognitive achievement consist of standardized reading and math scores on tests developed especially for the ECLS-K but based on existing instruments.[8] All scores are normalized with a mean of 50 and standard deviation of 9 points.

The data include both household survey data for multiple children per class (6 on average for this analysis sample) and teacher surveys so that one can characterize a student's classmates and teacher. Specifically, information on classroom composition, teacher qualifications, class size, racial, gender and special education status of the class come from teacher reports while information on average income and evaluation and diagnosis of ADD come from parental reports. The panel nature of the data allows one to follow the same child over time and determine when he was evaluated and diagnosed with ADD. The data on classroom and teacher characteristics are more complete for reading classrooms than math classrooms.

I focus on diagnosis and not treatment because treatment is not reported before fifth grade and because diagnosis is arguably more exogenous than treatment in this context. The focus on diagnosis, not treatment, likely results in downward bias of the estimates.

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[8] These include: the Children's Cognitive Battery, Peabody Individual Achievement test –Revised, the Peabody Picture Vocabulary Test-3, Primary Test of Cognitive Skills and the Woodcock-Johnson Psycho-Educational Battery-Revised.

Though I use the eighth grade data to identify those diagnosed with ADD in the future (and therefore classified as undiagnosed currently), for the analysis sample I use only data on kindergarten through fifth grades. I do so for two reasons. First, data on behavior is not collected after fifth grade. Second, by definition the share of classmates with undiagnosed is ADD is zero for all those in eighth grade. As such, the measure of peers with undiagnosed ADD is collinear with the eighth grade fixed effect.

B. Characteristics of Children with ADD

Children with and without a diagnosis of ADD by eighth grade are similar in terms of racial composition, per capita household income, and school, teacher and classroom characteristics (Table 1). But those diagnosed by eighth grade are more likely to be male (74 percent) and more likely to have health insurance (.91 vs .84). In terms of child outcomes, children with ADD suffer worse reading test scores and worse ratings in terms of externalizing behavior. They are also less likely to be rated by their teachers as "always working to the best of their ability."

C. Characterizing Peers

Peer characteristics were measured from teacher and parent reports. From teacher reports, I generate measures of the gender and racial composition of the class as well as class size. These measures are based on the whole class. From parent surveys, I generate measures of the share of students in the class with diagnosed and undiagnosed ADD and the average income of the students in the class. These measures are based on the subset of the class included in the ECLS-K sample (6 on average). I classify a child as having undiagnosed ADD if he or she is diagnosed with ADD in the future but is not currently diagnosed. This classification assumes that children who are ultimately diagnosed with ADD display symptoms of the disorder prior to their diagnosis, which is consistent with the medical evidence. Indeed, a diagnosis of ADD requires that the child displayed at least some symptoms before age 7.

This characterization of peers with undiagnosed ADD introduces three sources of measurement error which will lead to a downward bias of any estimated effect. The first arises if those with undiagnosed ADD exhibit few symptoms prior to diagnosis. Even though evidence based on the ECLS-K and elsewhere suggests that on average, those with undiagnosed ADD are characterized by greater inattention, this will not necessarily hold for all children. For example, in the ECLS-K, among those who are not yet diagnosed with ADD but will be in the future, 40 percent reportedly "have trouble paying attention relative to other children their age" compared with 10 percent of those who are never diagnosed with ADD. Second, because students in the ECLS-K are only followed through eighth grade, students diagnosed with ADD later would be incorrectly classified as not having ADD. However, since data from NHIS suggests that most children with ADD are diagnosed by age 13 (corresponding to eighth grade), this should not introduce much error. The third source of measurement error results from the fact that this measure is derived from the parent surveys and thus are calculated over six children, on average, per class (average class size is 21).[9] Ammermueller and Pischke (2006) show that when peer characteristics are measured over a sub-sample of students in the class, estimates of peer effects will be biased down by a factor of $(N_{sample}-1)/(N_{actual}-1)$ which is 1/4 in this sample. This suggests that the instrumental variable estimates will be considerably larger than OLS estimates.

D. Variation in Peer Characteristics

Six percent of the children surveyed in the ECLS-K are diagnosed with ADD by eighth grade, consist with data from the NHIS. Diagnosis occurs roughly uniformly between kindergarten and fifth grades, dropping in eighth grade. Of those ever diagnosed with ADD, 20 percent are diagnosed by kindergarten, another 22 percent are diagnosed in first grade, 25 percent between first and third grades, 21 percent between third and fifth grades and 12 percent between fifth and eighth grades. This generates variation in the share of classmates with diagnosed and undiagnosed ADD over time in this sample. For the sample of students without ADD, 28 percent have peers with undiagnosed ADD in kindergarten, in first grade 20 percent have peers with undiagnosed ADD, dropping to 11 percent in third grade, 4 percent by fifth grade, and (by definition) no students have peers with undiagnosed ADD in eighth grade. There are two sources of this variation: 1) undiagnosed peers are diagnosed, 2) undiagnosed peers change classrooms or attrit from the sample. While attrition is minimal up until third grade and the characteristics of the remaining sample remain stable, this changes in fifth grade: attrition increases and the characteristics of the remaining students change, they are less likely to be black and more likely to be upper income (Table 2).

[9] The ECLS K users manual chapter 4 describes the sample design. Within each school a self weighting sample of students was selected in Kindergarten. The only subgroup that was oversampled was Asian Pacific Islanders.

In the analyses I address the potential bias arising from non-random resorting of students with undiagnosed ADD and attrition.

V. Impact of Diagnosis on Own Cognitive and Behavioral Outcomes

To estimate whether diagnosing a child with ADD affects his own behavior and achievement, I compare outcomes for the same child before and after a diagnosis. To do so, I regress achievement and behavioral outcomes on an indicator for whether the child has been diagnosed with ADD, grade fixed effects, child fixed effects and time-variant family income, (Table 3, panel A). It is important to note that students diagnosed with ADD may become eligible for special education services at the same time – either because ADD makes them eligible for special education or because they are diagnosed with additional learning disabilities at the same time. If so, it may be the special education designation which affects outcomes, not diagnosis of ADD. As a result I also control for special education designation in these regressions. In panel B I include observed teacher and classroom characteristics (class size, masters degree, years of teaching experience, average income of classmates, share female, black and Hispanic) as controls. Finally, in panel C, I test whether diagnosis affects future test scores and behavior.

It may be, however, that any estimated impact of diagnosis and presumed treatment of ADD on outcomes simply reflects the fact that the child has been professionally evaluated. The act of evaluation may signal the presence of a concerned care-giver or some positive change in family circumstances which could explain the results. To address this I also present results from a "placebo test" of sorts by estimating the impact of being evaluated for ADD but not diagnosed on outcomes. The lack of any impact on behavior associated with evaluation but not diagnosis addresses the concern that underlying differences in care-seeking behavior of parents might bias the estimated impact of diagnosis. This also addresses the concern that children are diagnosed with ADD shortly after an increase in disruptive behavior and as such, the behavior might improve afterward due to mean-reversion, not treatment. If this were so, we would expect improvements in behavior among those evaluated but not diagnosed as well.

The results presented in Table 3 suggest that diagnosing a child with ADD does not appear to improve reading or math test scores but does improve behavior, decreasing the child's score on the "externalizing behavioral problem" scale by between 9 and 13 percent of a standard deviation, depending on the specification. This is consistent with the large medical literature and small economics literature on the topic which has generally found that treatment for ADD results in improved behavioral outcomes but little or no change in achievement, presumably due to "cognitive toxicity" associated with high levels of medication prescribed to maximize behavioral outcomes at the expense of cognitive ones. Evaluation but no diagnosis (columns 4-6) has no significant impact on either test scores or behavior in any specifications, suggesting that neither care-seeking behavior nor mean reversion are driving these results. In the next section I present the results of an analysis of the externalities associated with undiagnosed ADD.

VI. Empirical Results: Externalities Associated with ADD

Before turning to the main analysis of externalities, I present preliminary suggestive evidence of a negative externality associated with undiagnosed ADD. If children with undiagnosed ADD generate negative externalities, these externalities should decline over time as diagnosis and treatment increase. In Table 4 column (1) I present results from a regression of reading test scores on the share of classmates with ADD (that is, who are ever diagnosed with ADD), grade level and an interaction between the two. For this analysis, the sample includes only those without ADD (those never diagnosed with ADD). In addition to individual fixed effects, I also include controls for class size, share black, Hispanic and female, average income of classmates, and the share of special education students in class.

The estimated effect of having classmates with ADD is negative, but it declines significantly with grade progression. This is consistent with a hypothesis of peer behavior affecting cognitive achievement since children are increasingly diagnosed over time and diagnosis improves behavior. In columns 2 and 3 I drop the fifth grade and classes with special education students, respectively, and the results remain or increase slightly. In columns 4 and 5 I stratify by gender: the effects are larger for boys than girls, I point to which I return.

A. Fixed Effects Estimation - Strategy

To estimate the impact of peers who exhibit disruptive behavior on student achievement, I estimate the following equation for the sample of students in grades K-5.

$$Y_{ig} = \alpha + \beta_1 ADD\text{-}UNDIAG_{-icg} + \beta_2 X_{ig} + \beta_3 C_{-icg} + \beta_4 G_g + \beta_5 u_i + \varepsilon_{ig} \qquad (2)$$

Where *i* indexes individual students, *g* grade and *c* classroom. Y_{ig} in the above equation refers to reading or math test scores taken in the Spring of each year; $ADD\text{-}UNDIAG_{-icg}$ refers to the share of classmates with undiagnosed (and therefore untreated) ADD excluding the focal child. X_{ig} refers to time varying student characteristics such as age, family income, whether diagnosed with ADD, whether designated special education; C_{-icg} is a vector of classroom characteristics calculated over all students except the focal student and includes the share black, Hispanic and white, share female, share with special education, average income and class size as well as teacher characteristics (years of experience, having a master's degree and license); G_g refers to a grade fixed effect (first, third and fifth grades – kindergarten omitted) and u_i to individual fixed effects. All regressions are weighted by the number of students sampled in the class and the standard errors are clustered on the classroom.

The inclusion of individual fixed effects enables one to control for two important sources of omitted variables that could bias estimates of peer effects. The first is non-random selection into schools. The second is unobserved differences in family background of the child. However, as previously noted there are two potential threats to identification that the fixed effect does not address. In the next section I describe these threats and provide evidence that they likely do not bias the estimates.

B. Endogenous Diagnosis and Dynamic Sorting of Students

The two potential threats to identification are endogenous timing of diagnosis and dynamic sorting of students over time (see Rothstein, forthcoming). The former refers to the fact that the timing of diagnosis could be correlated with changes in teacher or peer characteristics that could affect reading test scores directly in which case the resulting estimates would be biased. For example, it could be that if the ability of one's peers improves, the likelihood of diagnosis increases as the student is viewed as an outlier. To address this I estimate discrete time hazard models to time of diagnosis to determine whether observed characteristics are associated with timing of diagnosis for the sample of children diagnosed with ADD by eighth grade. These characteristics include multiple measures of teacher quality (master, experience, licensure), classroom characteristics (gender, racial and income composition, share of class with ADD), peer quality (average lagged reading scores) and one's own lagged reading test scores. The results are presented in Table 5. Age is the only significant predictor of diagnosis. None of the other included variables are statistically or economically significant. Most notably, the past cognitive achievement of peers does not predict timing of diagnosis, nor does one's own past reading scores (the latter of which, if predictive, could be indicative of an Ashenfelter dip). The three measures of teacher quality (years of experience, licensure or masters degree) also have no statistically significant effect. The only other significant predictor of ADD diagnosis is special education designation, which is not surprising given that a diagnosis of ADD often qualifies a child for special education services (which is why it is important to control or special education status of the focal student and his peers in the regressions).

Regarding the second threat to identification (dynamic sorting of students over time), the concern is that diagnosis of ADD and an improvement in behavior may result in assignment to another class and thus different peers. To address this I examine changes in peer characteristics (share of special education students in the class, share Hispanic, black and female, average externalizing behavior scores, average lagged reading scores, and log income) before and after a diagnosis of ADD (Table 6). In all cases, changes in these characteristics are small and in all cases but one (share Black) insignificant.[10] Most notably, the average quality (as measured by lagged reading test scores and prior externalizing behavior problems) of a student's peers do not change after a diagnosis of ADD.

Related to this, school administrators may non-randomly sort students across classrooms within grade based, in part, on cognitive ability or behavior. School administrators might, for example, assign low ability students to classrooms characterized by more behavioral problems or to low quality teachers. To address this, I estimate whether teacher quality or lagged peer reading test scores predict the share of students in one's current class with undiagnosed ADD (Table 7). There are two significant predictors of share of students with undiagnosed ADD. The first is whether the teacher has a master's degree (though the magnitude is very small, essentially zero) and the second is the share of females which is negatively related to share undiagnosed. In columns 2 and 3 I include a student's own lagged score and the lagged score of current peers, respectively, and neither is related to the share undiagnosed. Finally in column 4 I control for

[10] Even for share Black, the difference (-.02) is relatively small (the average share black in the class in these data are .18) and we might expect that in testing 7 characteristics, one would be statistically significant by chance.

share with ADD (that is, ever diagnosed with ADD) and the statistically significant coefficient on share female falls by two thirds and is no longer significant. This suggests that the previously significant negative effect of share female simply reflected the fact that those with ADD (and therefore undiagnosed ADD) are predominantly male.

Together these estimates suggest that any non-random resorting of students over time based on past achievement, past behavior or teacher quality is not correlated with diagnosis of ADD. While we can only test whether observable measures of teacher and peer quality are correlated with diagnosis, the fact that they do not suggests that observable measures are unlikely to be either.

C. Fixed Effects Estimation – Classroom Level Results

The results from estimating equation (2) are presented in Table 8A. As the share of students in one's class with undiagnosed ADD increases, the reading test scores of his classmates decline (column 1). Because ADD is a condition that disproportionately affects boys and peer groups are largely gender specific at this age, one might expect the impact to be greater among other boys in the class (results in Table 4 also suggest greater effects for boys). In column (2) are results from a regression that also includes an interaction between share undiagnosed and male: the impact is much greater for boys than girls for whom there is no significant effect. In column 3 I control for the share of students with ADD (ever diagnosed with ADD) which appears to have no impact on reading test scores itself, nor does it change the impact of share with undiagnosed ADD (the point estimate for the main effect actually increases, though is still insignificant). This null effect for share with ADD is likely due to the inclusion of individual (and therefore school) fixed effects which greatly reduces variation in this measure.

To address the possibility that children may be sorted in classrooms according to past achievement and that this sorting may be correlated with the timing of diagnosis, I present results that include (in addition to the individual child fixed effects) the child's reading score in the previous survey period in column 4 and the reading test scores of peers in column 5. These regressions must exclude all kindergarten students. The estimated coefficient on the term share undiagnosed*male is larger once I control for lagged reading scores, suggesting that if there is any sorting on past achievement, it is not driving the results. Note that the estimated coefficient is larger only because the sample changes (excludes kindergarten).

While the estimated coefficient on the interaction term share undiagnosed*male is negative and significant, the estimated impact is small. Recall, that due to measurement error in the construction of the measure of classmates with undiagnosed ADD, the OLS results are attenuated by a factor of four (Ammermueller and Pischke, 2006). Once we account for this, the estimates imply that if a boy moves from a classroom where 8.5 percent of the students have undiagnosed ADD to a class where all are diagnosed (the standard deviation in these data), his test scores will improve by 1 point, or 10 percent of a standard deviation, still a relatively small effect. However, in interpreting these estimates it is important to note that most education interventions yield very small test score gains (10-20 percent of a standard deviation) if any at all (see Hanushek, 2006).

One way to address the concern that the timing of diagnosis may be non random (eg, correlated with particularly good teachers or high achieving peers) is do drop observations from classrooms in which a child was diagnosed in that year. The results (column 6) are unchanged when I do so. In column 7 I present estimates of equation (2) for reading test scores weighted by the share of the class surveyed. The results are not sensitive to this change in weighting. Finally, in column 8 I present results for math test scores. As noted previously, fewer children in the ECLS-K have complete information on the composition of their math classrooms, so the sample size declines. However, the results are fairly similar for reading and math scores.

In Table 8B I present estimates for equation (2) based on alternative samples as part of a series of robustness checks. In column 1 I limit the samples to males and control for school*cohort-specific trends in female test scores and the results are unchanged, which is consistent with the finding, not presented, that the rate of diagnosis over tiem in a school is uncorrelated with growth in test scores among girls. In column 2 I drop the fifth grade from the sample to see whether the results are driven by non-random attritions starting in the fifth grade – they are not. Finally, in column 3 of Table 8B I present results of a “placebo test.” I regress reading test scores on the share of students in the class evaluated for ADD but not diagnosed, and its interaction with male. Coefficients on the main term and the interaction term are small and imprecise, as expected.

D. Fixed Effect Estimation – Grade Level Results

Finally, I redefine the measure of the share of peers with undiagnosed ADD to be taken over all students in the grade, not just the classroom. This specification addresses the potential issue of non-random classroom assignment of students with undiagnosed ADD. Results presented in column 1 of Table 9 are based on the entire sample and in column 2 I limit the sample to males. In these two specifications I also exclude all classroom and teacher characteristics. Because of this, the sample sizes increase slightly because I include children in classrooms with missing information on teacher or classroom characteristics. In column 3 I control for all observable classroom and teacher characteristics as well as the average reading test scores of girls in the same school and grade.

The estimated effect roughly doubles in size when the share of peers with undiagnosed ADD is measured over the entire grade, not just the classroom. This difference in estimates based on the grade versus the classroom is likely attributable to two things: measurement error which decreases when I expand the sample over which to calculate a low probability event and endogenous sorting across classrooms within grades that biases downward the fixed effect estimates based on measures of the share undiagnosed in the classroom. If the latter, it would have to be the case that student quality is negatively correlated with the share of peers with undiagnosed ADD. However, in previous results (Tables 6 and 7) I found no evidence of a correlation between past achievement and the current share of the class with undiagnosed ADD. Thus, the former explanation, measurement error, seems most likely.

E. Why Peer Behavior Matters

Peer behavior may affect student cognitive achievement through three potential channels. First, there may be "contagion" effects whereby the disruptive behavior of a peer may induce negative behavior in others. I find no evidence of "contagion" effects in the data: having peers with undiagnosed ADD does not increase students' externalizing behavioral problems. Second, disruptive behavior of a peer may distract classmates (a direct effect). The fact that the effects are concentrated among boys might be construed as evidence that the impact is working through direct disruption of other boys (eg friends). Finally, disruptive students may take up more teacher time, leaving less time for instruction (an indirect effect). In the next subsection I explore whether disruptive students affect their peers by diverting teacher resources. I do so by estimating whether the negative impact we observe declines with greater classroom resources. I find suggestive evidence that it does.

F. Undiagnosed ADD and Teacher/Classroom Characteristics

To explore whether resources can overcome negative peer effects, I re-estimate equation (2) including interactions between share undiagnosed and measures of classroom and teacher characteristics (Table 10). In columns 1-5 I present estimates based on the full sample and in columns 6-10 I limit the sample to males. Smaller class sizes can overcome the negative peer effects associated with untreated ADD. If there are 30 students in a class and the share undiagnosed declines by 8.5 percent, reading test scores would increase by 1.5 points.[11] But if there are only 20 students in the class, the impact drops to 0.4 points. This is consistent with both the model presented earlier and Lazear's (2001) disruption model of education production which stipulates that small class size mitigates the impact of disruptive peers on a student's ability to learn. There is little evidence that teacher human capital (specifically, possession of a graduate degree, years of experience or having an advanced license) can overcome negative peer effects, consistent with work by Hanushek and Rivkin (2004) showing that a master's degree is a poor predictor of teacher quality.

In the next section, I relax the assumption of the exogeneity of the timing diagnosis of ADD entirely, relying instead on instrumental variables for identification of the impact of classmates with undiagnosed ADD on reading test scores.

VII. Instrumental Variable Estimates

A. Instruments for Classmates with Undiagnosed ADD

To instrument for the share of the class with undiagnosed ADD, I use recent expansions in eligibility for publicly provided child health insurance (SCHIP).[12] In 1997 Congress authorized SCHIP, greatly expanding children's eligibility for publicly provided health insurance. Though SCHIP was federally authorized and subsidized, individual states were free

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[11] This calculation accounts for measurement error, multiplying the estimated effect by 4.

[12] I cannot instrument for externalizing behavioral problems of classmates because the first stage is too weak: SCHIP/Medicaid eligibility levels are not strong predictors of externalizing behavioral problems, which is not surprising given that behavioral problems likely have many causes, only some of which may be amenable to medical treatment (and thus greater insurance coverage).

to develop their own SCHIP programs, subject to federal approval. As a result there was considerable heterogeneity in both the timing and scope of SCHIP programs across the states on which I rely to identify the impact of SCHIP on diagnosis. Thirty-seven percent of the children in the analysis sample are eligible for SCHIP.

The underlying assumption of using SCHIP eligibility expansions as an instrument for share undiagnosed is that by increasing health insurance coverage, SCHIP expansions lower the cost of medical care, thereby lowering the cost of a medical diagnosis of ADD. In section IX of the paper, I provide evidence supporting the use of SCHIP eligibility expansions as an instrument in this context. I do so by establishing that SCHIP eligibility significantly increased the probability of ADD diagnosis via increases in health insurance coverage.

Another necessary assumption is that SCHIP has no direct or independent effect on student achievement (the exclusion restriction). The concern is that the expansion in public health insurance could directly improve student health and cognitive achievement, though the evidence linking physical health and achievement is very limited. Levine and Schanzenbach (2009) estimate the direct reduced form impact of SCHIP expansions on cognitive achievement and do not find any contemporaneous effects. Rather, the only economic and statistically significant effects operate though improved health at birth, which is not an issue in this context as all children in the ECLS-K are born before the expansions.

B. IV Estimates of the Impact of Undiagnosed ADD on Peer Reading

The first stage results of the IV analysis are presented in Appendix Table 1. The instruments for the share of classmates with undiagnosed ADD are the Medicaid/SCHIP eligibility thresholds in the state and year and the threshold interacted with the child's age. The endogenous variable is measured two ways: share of classmates with undiagnosed add (column 1 Appendix Table 1) and share of those with ADD who are undiagnosed (column 2 Appendix Table 1). The latter is set to zero in classes that have no students with ADD. The IV regressions include all covariates included in the previous OLS regressions, including the individual fixed effects.[13] The results of the first stage suggest that the increase in the eligibility threshold reduces the share of the class with undiagnosed ADD, with the impact increasing with age of the child.

[13] The IV regressions are unweighted because weighting led to less precise first stage estimates (a weaker first stage)

For example, increasing the threshold from 100 to 300 percent of the federal poverty line will reduce the share of the class with undiagnosed ADD by 12 percent (column 1). The same increase in eligibility thresholds will reduce the share of those with ADD who are undiagnosed by 10 percent (column 2).

The second stage estimates of the impact of peers with undiagnosed ADD on reading test scores are presented in Table 11. The results for math scores are large but imprecise and therefore not presented here. I follow the method outlined in Newey, Powell and Vella (1999) for instrumenting for endogenous interactions (share undiagnosed*male).[14] As with the OLS fixed effect estimates I define the sample multiple ways: columns 1 and 5 contain estimates based on the full sample, columns 2 and 6 include the lagged reading test score (value added model), columns 3 and 7 exclude special education students and columns 4 and 8 exclude special education and 5th grade.

The results are generally consistent across the different specifications. As with the OLS fixed effect estimates, the interaction term (share undiagnosed*male) is negative and significant in most specifications while the main effect is always insignificant, though it varies in magnitude.[15] The one insignificant effect occurs when I exclude the fifth grade and the sample falls by almost a third in column 4 (though it remains significant in column 8.) The results generally imply that if the share of peers with undiagnosed ADD falls by .085 (the standard deviation), test scores will increase by 1.3 points, or 15 percent of a standard deviation. The results in column 5-8 based on the alternative measure of undiagnosed peers, suggest that going from a class in which all those with ADD are undiagnosed to one in which they are all diagnosed will increase test scores by 2 points, or 22 percent of a standard deviation. These estimates represent a moderate effect given previous work estimating that a one standard deviation increase in peer cognitive achievement increases student achievement by 35 percent of a standard deviation (Hanushek et al, 2003).

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[14] This method involves estimating a first stage (regressing the share of peers with undiagnosed ADD on the instruments and other exogenous variables), generating a predicted value and a residual, interacting the predicted value and residual with male, and regressing the outcome (reading test scores) on the predicted value, its interaction, the residual and its interaction in a second stage regression. The standard errors are bootstrapped.

[15] For the full sample, the estimate of the interaction term is -14 and significant while the estimate of the main term is 10.8, large, positive and insignificant. The positive estimate on the main term seems to be driven by the 1500 special education students: when they are removed in column 3, the interaction term remains, but the main effect falls to 1.86.

VIII. Cost Benefit Analysis

The benefits of treating children with ADD in terms of the reduced externalitites on peers' cognitive achievement exceed the costs of treatment. The costs of treating two children for one year are roughly $1100. To assess the cost-effectiveness of treatment, I first compare the costs of treatment with the costs of directly increasing the reading test scores of a student by 0.2 standard deviation (the upper bound of estimated peer effect associated with reducing classroom disruption via treatment of students with ADD). Hedges et al (1994) estimate that it costs $500 per student to raise scores by 0.7 of a standard deviation. Assuming that the costs calculated by Hedges are linear, it would cost $1430 to directly increase the test scores of 10 boys by 0.2 of a standard deviation which exceeds the $1100 needed to treat two boys with ADD. Alternatively, and perhaps preferably, one can calculate the benefits of improving test scores by examining the increase in wages associated with an increase in cognitive test scores at age 7.[16] According to this calculation, increasing peer test scores by 0.2 of a standard deviation at age 7 leads to a 0.6 percent increase in annual adult wages per peer, or roughly $215 annually. Assuming 10 male peers, this amounts to $2150 annually. Compared with a one-time cost of $1100 (or even $1100 annually for 12 years of school), the lifetime benefits associated with improving the cognitive achievement of peers are substantial, even after discounting future benefits. Regardless of the methods of calculation, treating children for ADD and thereby improving their behavior is a cost effective method of reducing the negative externalities imposed on others in terms of human capital accumulation and, ultimately, worker productivity and earnings.[17]

IX. SCHIP Eligibility, Insurance Coverage, and Diagnosis of ADD

In this section I provide evidence to support using SCHIP eligibility expansions to instrument for share with undiagnosed ADD. The underlying assumption behind this instrument

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[16] This calculation is based on Currie and Thomas (2001). They find, based on data from UK, that a one standard deviation increase in reading test scores at age 7 lead s to .448 percent of an increase in reading test scores at age 16 and that a one standard deviation increase in test scores at age 16 leads to a 6 percent increase in wages at age 33. Based on this I calculate that a .2 standard deviation increase in test scores at age 7 leads to a 0.6 percent increase in earnings at age 33. Based on median annual wages of 40,000 (the 2007 average wage index calculated by the Social Security Administration) this represents roughly $215 annually.

[17] This calculation ignores any positive benefit of treatment for the child with ADD and thus represents a lower bound.

is that by increasing health insurance coverage, SCHIP expansions lower the cost of medical care thereby lowering the cost of a diagnosis of ADD. I show that SCHIP eligibility increases the probability of health insurance coverage and increases the probability of a diagnosis of ADD in individual fixed effect regressions.

I first show that eligibility for SCHIP is associated with health insurance coverage and diagnosis by estimating the following equation:

$$Y_{it}= \alpha + \beta_1 Eligble_{it} + \beta_2 Eligible_{it}*age + \beta_2 age_{it} + \beta_3 \ln(income)_{it} + \beta_4 grade_t + u_i + \varepsilon_{it} \quad (3)$$

Where Y is an indicator for any health insurance or for being diagnosed with ADD, depending on the regression; eligible is an indicator equal to one if the child is eligible for SCHIP and is interacted with age; income, age, and grade controls are included as well as individual fixed effects. The instruments for eligible and eligible*age in the above equation are the state SCHIP eligibility level (as a percent of the federal poverty line for a child of that age in that state) and the SCHIP eligibility level interacted with age. The first stage of this regression is presented in columns 4 and 5 of Appendix Table 2: expanding eligibility thresholds significantly increases the probability that a child will be eligible for SCHIP.

IV estimates suggest that becoming eligible for SCHIP does increase health insurance coverage and diagnosis (columns 1 and 2 of Appendix Table 2). For diagnosis, the impact of SCHIP eligibility increases with age. In column 3 I present reduced form estimates of the impact of SCHIP eligibility levels as a function of the FPL on the probability of diagnosis: increasing eligibility threshold from 100 to 200 percent of the federal poverty level increases the probability of diagnosis by .5 percentage points for five year olds and one percentage point for ten year olds. This represents a reasonable effect given an underlying rate of diagnosis of five percent for ten year olds.

X. Conclusions

After establishing that peer achievement affects student achievement, the literature is increasingly turning to understanding the mechanism(s) underlying the relationship. Peer achievement may matter because high achieving peers are smarter (more able) or exert greater effort and concentration and are less disruptive in class (better behaved). In this paper I use a unique identification strategy to identify the impact of classmate behavior relative to classmate cognitive ability on achievement. Children with ADD are more likely to have behavioral problems. Once diagnosed, however, their behavior improves, but their achievement is unchanged, presumably due to declines in cognitive ability. In individual fixed effect regressions, I find that the classmates of those with undiagnosed ADD suffer worse scores on reading and math achievement tests, but the results are concentrated among boys. I develop a simple theoretical model of peer effects that makes explicit what assumptions regarding the education production function would be consistent with the empirical finding that diagnosis does not improve one's own achievement but does improve the achievement of one's peers.

These results are robust to a number of alternative specifications and instrumental variable estimation. I also find that resources such as class size can overcome the negative peer effects observed, consistent with the "disruption" model of education production proposed by Lazear (2001). Finally, a cost benefit analysis finds that the costs of treating children with ADD are outweighed by the benefit if one considers these externalities.

These results have two important policy implications. First, the findings that resources both affect peer behavior (via treatment) and mitigate the negative externalities associated with disruptive behavior (via greater classroom resources) suggest that peer effects should be considered within their institutional framework. As such, policy discussions need not be limited to how best to compose classrooms to maximize peer effects. Rather, policies that also consider the ways in which teacher, school, and community resources (health care in this case) influence or mitigate peer effects via student behavior may ultimately be easier to implement and just as effective. A second implication regards the relationship between health, productivity and growth. These results suggest that mental health may affect growth, through both its impact on the human capital accumulation of those with a mental disorder and the externalities imposed on others.

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Table 1 Summary Statistics Stratified by Whether Child Ever Diagnosed (by Eighth Grade) with ADD/ADHD

	All		Male	
	Never Diagnosed	Diagnosed	Never Diagnosed	Diagnosed
Male	0.49	0.74		
Black	0.13	0.12	0.13	0.11
Hispanic	0.17	0.10	0.17	0.1
Any Insurance	0.84	0.91	0.84	0.91
Medicaid	0.19	0.26	0.19	0.26
Family Income	$75,903	$69,425	$76,621	$69,358
Public School	0.80	0.84	0.8	0.85
Catholic School	0.11	0.10	0.11	0.09
Class size	21.40	20.40	21.2	20.2
Teacher has masters	0.34	0.37	0.34	0.38
Share black in class	0.11	0.12	0.11	0.11
Share female in class	0.49	0.48	0.48	0.47
Reading test score	51.10	46.46	50.3	46.3
Math test score	50.97	46.45	51.52	47.13
Self control (scale 1-4)	3.22	2.77	3.12	2.72
Externalizing behavior problelms (scale 1-4)	1.63	2.16	1.75	2.24
Always works to best of Ability	0.25	0.06	0.192	0.05

Table 2 Follow up of the 19,990 Students Interviewed in Kindergarten

Last grade observed	Observations	Income	Male	Black	diagnosed with ADD
Kindergarten	3940	$68,842	0.51	0.17	0.02
First	2310	$70,499	0.53	0.22	0.04
Third	2850	$70,137	0.53	0.21	0.07
Fifth	2230	$69,680	0.51	0.17	0.06
Eighth	8660	$80,364	0.50	0.11	0.08
Total	19990				

Table 3 Impact of Diagnosis on Own Outcomes

	Diagnosed with ADD			Evaluated for ADD, Not Diagnosed		
Panel A Excluding Class Characteristics	**Read**	**Extern BPI**	**Math**	**Read**	**Extern BPI**	**Math**
ADD	0.103	-0.075	0.316	-0.303	0.026	-0.111
	[0.326]	[0.031]	[0.273]	[0.209]	[0.019]	[0.189]
Child age	-1.249	0.03	-0.414	-1.249	0.029	-0.41
	[0.297]	[0.019]	[0.233]	[0.296]	[0.019]	[0.233]
Ln(family income)	0	-0.005	-0.034	-0.002	-0.005	-0.035
	[0.071]	[0.007]	[0.068]	[0.071]	[0.007]	[0.068]
First grade	2.376	-0.047	0.53	2.386	-0.048	0.532
	[0.532]	[0.035]	[0.420]	[0.532]	[0.035]	[0.419]
Third grade	4.866	-0.052	1.26	4.895	-0.054	1.267
	[1.125]	[0.074]	[0.884]	[1.124]	[0.074]	[0.883]
Fifth grade	7.584	-0.149	2.248	7.627	-0.152	2.259
	[1.707]	[0.112]	[1.341]	[1.706]	[0.112]	[1.338]
Observations	49410	46710	50090	49410	46710	50090
R-squared	0.84	0.72	0.87	0.84	0.72	0.87
Panel B Including Class Characteristics						
ADD	-0.004	-0.061	0.13	-0.286	0.031	0.066
	[0.354]	[0.034]	[0.357]	[0.225]	[0.020]	[0.250]
Observations	44770	43930	37130	44770	43930	37130
R-squared	0.84	0.73	0.88	0.84	0.73	0.88
Panel C Impact on Future Outcomes & Including Class Characteristics						
ADD	-1.341	-0.089	0.003	0.177	-0.021	-0.274
	[0.490]	[0.058]	[0.478]	[0.304]	[0.034]	[0.346]
Observations	38500	27760	25540	38500	27760	25540
R-squared	0.84	0.77	0.92	0.84	0.77	0.92

Robust standard errors clustlered on child in brackets

All regressions include individual child fixed effects

Class characteristics included in panels B and C include share black, share hispanic, share female, whether teacher has masters, full license, teacher's years of experience, share of class with special education services, class size, whether child designated special ed

Table 4 Impact of Share Ever Diagnosed with ADD on Reading Test Scores of Peers Over Time

	All	Drop 5th	Drop Spec. Ed	Female	Male
Share of class ever diagnosed with ADD	-2.347	-3.416	-2.669	-1.872	-2.846
	[0.914]	[1.300]	[0.961]	[1.105]	[1.116]
Share ever diagnosed*grade	0.815	1.541	0.997	0.451	1.179
	[0.324]	[0.592]	[0.348]	[0.398]	[0.394]
Grade	0.17	0.082	0.18	0.142	0.208
	[0.064]	[0.103]	[0.065]	[0.078]	[0.074]
Teacher has masters degree	0.158	0.261	0.175	0.082	0.236
	[0.123]	[0.149]	[0.128]	[0.143]	[0.148]
Teacher has license	-0.021	0.045	-0.061	0.063	-0.109
	[0.179]	[0.207]	[0.184]	[0.215]	[0.205]
Teacher years of experience	0.012	0.009	0.013	0.003	0.021
	[0.008]	[0.011]	[0.009]	[0.010]	[0.010]
Class size	-0.039	-0.051	-0.038	-0.032	-0.047
	[0.016]	[0.020]	[0.016]	[0.018]	[0.020]
Share Hispanic students in class	-0.181	0.027	-0.213	-0.234	-0.164
	[0.424]	[0.457]	[0.434]	[0.482]	[0.557]
Share black students in class	-1.686	-1.409	-1.66	-1.51	-1.871
	[0.345]	[0.383]	[0.354]	[0.414]	[0.426]
Share female in class	0.56	0.468	0.528	0.549	0.585
	[0.555]	[0.695]	[0.567]	[0.687]	[0.718]
Class avg. income (in $10000)	-0.026	-0.037	-0.026	-0.05	-0.002
	[0.019]	[0.022]	[0.020]	[0.023]	[0.025]
Classroom characteristics missing	0.15	0.24	0.161	0.151	0.157
	[0.170]	[0.208]	[0.175]	[0.204]	[0.203]
Student in Special Ed	-0.416	-0.264		0.479	-0.924
	[0.245]	[0.309]		[0.382]	[0.319]
Share Special Ed in class	0.691	0.847		0.68	0.655
	[0.365]	[0.514]		[0.470]	[0.477]
Observations	47830	39750	46090	23790	24040
R-squared	0.84	0.87	0.84	0.84	0.85

Robust standard errors clustered on classroom in brackets

All regressions include individual child fixed effects

Table 5: Preidctors of ADD Diagnosis: Hazard Models

	(1)	(2)	(3)	(4)	(5)
Child age	0.073	0.067	0.068	0.056	0.053
	[0.026]	[0.026]	[0.027]	[0.037]	[0.037]
Ln(income)	-0.051	-0.05	-0.051	-0.019	-0.019
	[0.011]	[0.011]	[0.011]	[0.020]	[0.021]
Teacher has masters degree	0.029	0.027	0.027	0.048	0.044
	[0.022]	[0.022]	[0.022]	[0.030]	[0.030]
Teacher has license	0.001	0	0.001	0.011	0.016
	[0.031]	[0.031]	[0.031]	[0.047]	[0.048]
Teacher years of experience	0.002	0.002	0.002	0.002	0.002
	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Class size	-0.002	-0.002	-0.002	-0.002	-0.001
	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Share Hispanic students in class	-0.074	-0.079	-0.075	-0.091	-0.105
	[0.047]	[0.048]	[0.050]	[0.078]	[0.080]
Share black students in class	-0.009	-0.01	-0.007	0.019	0.025
	[0.050]	[0.050]	[0.052]	[0.075]	[0.077]
Share female in class	-0.095	-0.07	-0.057	-0.121	-0.13
	[0.103]	[0.103]	[0.108]	[0.152]	[0.154]
Class avg. income in $10000	-0.002	-0.002	-0.002	-0.003	-0.003
	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]
Classroom characteristics missing	0.053	0.04	0.039	0.04	0.049
	[0.033]	[0.034]	[0.039]	[0.050]	[0.051]
First grade	-0.043	-0.043	-0.044		
	[0.054]	[0.053]	[0.054]		
Third grade	-0.032	-0.029	-0.03	0.053	0.058
	[0.106]	[0.105]	[0.108]	[0.083]	[0.083]
Fifth grade	0.073	0.086	0.085	0.194	0.208
	[0.160]	[0.158]	[0.161]	[0.155]	[0.156]
Eighth grade	0.139	0.179	0.181	0.331	0.347
	[0.236]	[0.234]	[0.239]	[0.262]	[0.263]
Student designated Special Ed		0.097	0.101	0.065	0.076
		[0.039]	[0.041]	[0.043]	[0.045]
Share Special Ed in class		-0.014	-0.031	-0.051	-0.069
		[0.076]	[0.080]	[0.083]	[0.088]
Share of class ever diagnosed with ADD			0.061	0.096	0.103
			[0.061]	[0.073]	[0.075]
Lagged reading test score				-0.003	-0.003
				[0.002]	[0.002]
Lagged Reading Scores of Current Classmates					0
					[0.003]
Observations	2870	2780	2460	1560	1500
R-squared	0.17	0.17	0.16	0.15	0.15

Robust standard errors clustered on classroom in brackets

All regressions include individual child fixed effects

Table 6 Change in Peer Characteristics After Diagnosis

	difference	t statistic
Share Special Education Students	0.0088	0.9
Share Hispanic	0.0032	0.56
Share Black	-0.012	2.16
Share Female	0.0038	0.62
Average Log Income	-0.003	0.02
Average Lagged Reading Test Scores of Classmates	0.192	0.37
Average Externalizing Behavioral Problems	0.011	0.42

Table 7: Predictors of Share Undiagnosed in Classroom

	(1)	(2)	(3)	(4)
Own lagged reading test score		0	0	0
		[0.000]	[0.000]	[0.000]
Lagged Reading Scores of Current Classmates			0	0
			[0.000]	[0.000]
Share of class ever diagnosed with ADD				0.401
				[0.019]
Child age	-0.002	-0.021	-0.021	-0.013
	[0.004]	[0.020]	[0.020]	[0.017]
Ln(family income)	0	0	0	-0.001
	[0.001]	[0.002]	[0.002]	[0.002]
First grade	-0.007	0	0	-0.016
	[0.007]	[0.000]	[0.000]	[0.067]
Third grade	-0.017	0.025	0.025	-0.007
	[0.014]	[0.040]	[0.040]	[0.033]
Fifth grade	-0.033	0.046	0.045	0
	[0.022]	[0.079]	[0.079]	[0.000]
Teacher has masters degree	-0.005	-0.007	-0.007	-0.006
	[0.002]	[0.003]	[0.003]	[0.003]
Teacher has license	0.004	0.003	0.003	0.002
	[0.003]	[0.004]	[0.004]	[0.004]
Teacher years of experience	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
Class size	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
% Hispanic students in class	0.018	0.033	0.034	0.02
	[0.014]	[0.019]	[0.020]	[0.016]
% black students in class	0.014	0.02	0.02	0.002
	[0.013]	[0.018]	[0.019]	[0.016]
% female in class	-0.029	-0.029	-0.029	-0.009
	[0.013]	[0.017]	[0.017]	[0.015]
Class avg. income in $10000	0	0	0	0.001
	[0.000]	[0.001]	[0.001]	[0.001]
Classroom characteristics missing	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]
Student in Special Ed	-0.001	-0.004	-0.003	-0.004
	[0.004]	[0.005]	[0.005]	[0.004]
Share Special Ed in class	0.007	0.023	0.023	-0.045
	[0.011]	[0.012]	[0.012]	[0.011]
Observations	37060	24640	23810	24540
R-squared	0.59	0.61	0.62	0.74

Robust standard errors clustered on classroom in brackets

Table 8A: Impact of Diagnosis on Classmate Reading Test Scores

	All	Interact Male	Share w/ADD	Own Lagged Read Score	Class Lagged Read Score	Drop Grade Dx	Reweight	Math
Share undiagnosed	-1.49	-0.713	-1.218	0.264	0.395	0.246	-0.776	0.374
	[0.576]	[0.744]	[0.884]	[0.886]	[0.908]	[0.949]	[0.752]	[0.738]
Share unidagnosed*male		-1.513	-1.498	-2.49	-2.843	-2.73	-1.609	-1.75
		[0.889]	[0.889]	[1.111]	[1.141]	[1.244]	[0.909]	[0.986]
Child age	0.015	0.014	0.015	0.112	2.268	2.532	0.03	0.088
	[0.082]	[0.082]	[0.082]	[0.148]	[1.249]	[1.340]	[0.082]	[0.104]
Ln(family income)	-0.971	-0.972	-0.972	2.253	0.118	0.092	-1.068	-1.032
	[0.393]	[0.394]	[0.394]	[1.241]	[0.151]	[0.158]	[0.413]	[0.304]
First grade	2.196	2.197	2.195		8.698	0	2.42	1.302
	[0.713]	[0.713]	[0.714]		[5.034]	[0.000]	[0.743]	[0.561]
Third grade	4.252	4.255	4.247	-4.434	4.228	-5.07	4.61	2.748
	[1.495]	[1.496]	[1.497]	[2.528]	[2.495]	[2.731]	[1.562]	[1.170]
Fifth grade	6.457	6.463	6.449	-8.633		-9.807	6.968	0
	[2.273]	[2.275]	[2.276]	[4.999]		[5.400]	[2.374]	[0.000]
Diagnosed with ADD/ADHD	-0.071	-0.085	-0.092	-0.456	-0.44	-0.245	-0.155	0.188
	[0.352]	[0.352]	[0.351]	[0.427]	[0.435]	[0.813]	[0.357]	[0.459]
Teacher has masters degree	0.019	0.018	0.017	-0.101	-0.104	-0.128	0.022	0.102
	[0.142]	[0.142]	[0.142]	[0.174]	[0.177]	[0.194]	[0.138]	[0.152]
Teacher has license	-0.157	-0.156	-0.156	-0.006	-0.027	-0.102	-0.11	-0.339
	[0.213]	[0.213]	[0.214]	[0.268]	[0.268]	[0.295]	[0.199]	[0.230]
Teacher years of experience	0.02	0.02	0.02	0.008	0.009	0.008	0.021	
	[0.009]	[0.009]	[0.009]	[0.011]	[0.011]	[0.012]	[0.010]	
Class size	-0.032	-0.032	-0.032	-0.012	-0.011	-0.018	-0.024	-0.037
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.019]	[0.017]	[0.021]
% Hispanic students in class	-0.506	-0.509	-0.505	0.337	0.528	0.733	-0.471	3.042
	[0.585]	[0.585]	[0.584]	[1.074]	[1.094]	[1.150]	[0.555]	[0.486]
% black students in class	-2.075	-2.077	-2.08	-0.034	0.088	0.026	-2.157	-0.863
	[0.490]	[0.490]	[0.490]	[1.079]	[1.100]	[1.169]	[0.480]	[0.506]
% female in class	0.805	0.806	0.822	1.456	1.4	1.143	0.874	
	[0.733]	[0.733]	[0.734]	[0.892]	[0.908]	[0.917]	[0.731]	
Class avg. income in $10000	-0.021	-0.022	-0.021	-0.017	-0.019	-0.002	-0.024	0
	[0.024]	[0.024]	[0.024]	[0.034]	[0.035]	[0.036]	[0.024]	[0.000]
Student in Special Ed	-0.056	-0.064	-0.063	-0.013	-0.048	-0.01	-0.185	0.603
	[0.311]	[0.310]	[0.310]	[0.390]	[0.400]	[0.430]	[0.316]	[0.375]
Share Special Ed in class	0.725	0.738	0.645	0.315	0.322	0.531	0.611	0.605
	[0.468]	[0.467]	[0.476]	[0.529]	[0.553]	[0.617]	[0.493]	[0.630]
Lagged Reading Scores of Current Classmates					0.047	0.054		
					[0.019]	[0.020]		
Lagged Reading Scores of Current Classmates* male					-0.053	-0.036		
					[0.024]	[0.024]		
Own lagged reading score				0.006		0.007		
				[0.018]		[0.019]		
Share of class ever diagnosed with ADD			0.61					
			[0.524]					
Observations	36050	36050	36050	24510	23700	22920	36050	29940
R-squared	0.85	0.85	0.85	0.87	0.87	0.88	0.85	0.9

Robust standard errors clustered on classroom in brackets

All regressions include individual child fixed effects

Table 8B: Impact of Diagnosis on Classmate Reading Test Scores - Alternative Specifications or Samples

	Males	Drop 5th Grade	Placebo
Share undiagnosed	-1.812	-0.471	
	[0.687]	[0.901]	
share unidagnosed*male		-1.447	
		[1.106]	
Girls reading test scores in school-grade	0.379		
	[0.026]		
Share of kids in class evaluated but not diagnosed			-0.19
			[0.558]
Share of kids in class evaluated but not diagnosed*male			-0.786
			[0.663]
Observations	17800	28850	36050
R-squared	0.86	0.88	0.85

Robust standard errors clustered on classroom in brackets
All regressions include individual child fixed effects and all controls included in Table 8A col 1

Table 9: Impact of Share Undiagnosed in Grade on Reading Test Scores

	All	Male	Males
Share of grade with undiagnosed ADD	-1.789	-4.825	-5.164
	[1.663]	[1.748]	[0.000]
Share of grade with undiagnosed ADD*Male	-3.452		
	[1.484]		
Percent black in grade	4.357	3.897	4.315
	[1.102]	[1.315]	[1.522]
Percent hispanic in grade	1.742	2.723	2.536
	[1.025]	[1.284]	[1.563]
Average income in grade	0	0	0
	[0.000]	[0.000]	[0.000]
Percent special ed in grade	1.275	1.433	1.989
	[0.965]	[1.174]	[1.247]
Percent male in grade	-1.154	-1.016	-1.426
	[0.759]	[0.921]	[1.159]
Teacher has masters degree	-0.171	-0.669	0.099
			[0.158]
Teacher has license			-0.247
			[0.237]
Teacher years of experience			0.027
			[0.011]
Class size			-0.027
			[0.022]
Percent Hispanic in class			0.803
			[0.844]
Percent black in class			-1.165
			[0.621]
Percent female in class			0.295
			[0.960]
Class avg. income in $10000			-0.005
			[0.026]
Student in Special Ed			-0.653
			[0.397]
Share Special Ed in class			-0.013
			[0.584]
Girls reading test scores in school*grade			0.386
			[0.028]
Observations	41630	20910	17470
R-squared	0.84	0.85	0.86

Robust standard errors clustered on school*grade in brackets
All regressions include individual child fixed effects and grade fixed effec

Table 10: Do Classroom Resources Moderate the Impact of Peer Behavior on Reading Test Scores?

	All					Males				
Share undiagnosed	-17.148	-1.983	-2.859	-15.04	-1.808	-21.352	-2.4	-4.013	-22.606	-2.29
	[9.741]	[0.779]	[1.678]	[9.654]	[0.933]	[12.458]	[0.932]	[2.240]	[13.844]	[1.089]
Share undiagnosed*Teacher has Masters	1.047	1.144				0.74	0.686			
	[1.132]	[1.134]				[1.344]	[1.377]			
Share undiagnosed*Teacher License	1.125		1.5			0.929		2.081		
	[1.885]		[1.799]			[2.315]		[2.356]		
Share undiagnosed*ln(40-Classize)	4.753			4.596		6.29			6.937	
	[3.238]			[3.255]		[4.147]			[4.664]	
Share undiagnosed*Teacher Experience	0.015				0.022	0.008				0.012
	[0.056]				[0.054]	[0.061]				[0.062]
Teacher has masters degree	-0.021	-0.034	0.007	0.019	0.006	0.124	0.052	0.076	0.088	0.076
	[0.147]	[0.148]	[0.142]	[0.141]	[0.142]	[0.181]	[0.180]	[0.172]	[0.172]	[0.172]
Teacher has license	-0.187	-0.152	-0.203	-0.15	-0.154	-0.052	-0.25	-0.315	-0.242	-0.251
	[0.235]	[0.214]	[0.234]	[0.215]	[0.214]	[0.235]	[0.250]	[0.268]	[0.251]	[0.250]
Teacher years of experience	0.022	0.022	0.022	0.022	0.021	0.017	0.03	0.03	0.03	0.03
	[0.009]	[0.009]	[0.009]	[0.009]	[0.010]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
Class size	-0.024	-0.031	-0.031	-0.024	-0.031	-0.019	-0.034	-0.034	-0.02	-0.034
	[0.015]	[0.016]	[0.016]	[0.015]	[0.016]	[0.018]	[0.022]	[0.022]	[0.020]	[0.022]
% Hispanic students in class	-0.393	-0.36	-0.369	-0.398	-0.364	-0.663	-0.092	-0.108	-0.142	-0.097
	[0.579]	[0.580]	[0.579]	[0.579]	[0.580]	[0.708]	[0.790]	[0.789]	[0.786]	[0.790]
% black students in class	-2.154	-2.001	-1.986	-2.148	-1.984	-2.097	-1.869	-1.86	-1.905	-1.86
	[0.485]	[0.489]	[0.488]	[0.485]	[0.489]	[0.573]	[0.632]	[0.630]	[0.630]	[0.631]
% female in class	0.827	0.821	0.812	0.829	0.812	0.941	0.824	0.823	0.835	0.821
	[0.733]	[0.733]	[0.734]	[0.733]	[0.734]	[0.937]	[0.987]	[0.987]	[0.982]	[0.988]
Class avg. income in $10000	-0.022	-0.023	-0.023	-0.022	-0.023	0.004	-0.001	-0.001	0	-0.001
	[0.024]	[0.024]	[0.024]	[0.024]	[0.024]	[0.029]	[0.031]	[0.031]	[0.031]	[0.031]
Student in Special Ed	-0.069	-0.067	-0.075	-0.08	-0.075	-1.254	-0.558	-0.561	-0.574	-0.562
	[0.310]	[0.312]	[0.312]	[0.310]	[0.312]	[0.443]	[0.403]	[0.403]	[0.396]	[0.403]
Share Special Ed in class	0.809	0.798	0.792	0.798	0.79	0.518	0.865	0.864	0.872	0.861
	[0.468]	[0.466]	[0.466]	[0.468]	[0.466]	[0.536]	[0.601]	[0.601]	[0.603]	[0.601]
Observations	36030	36050	36050	36030	36050	18010	18020	18020	18010	18020
R-squared	0.85	0.85	0.85	0.85	0.85	0.83	0.85	0.85	0.85	0.85

Robust standard errors clusterd on classroom in brackets
Also included are grade dummies, age of student, income of student, whether student diagnosed with ADD
All regressions include individual child fixed effects

Table 11: IV Impact of Undiagnosed ADD on Others' Reading Test Scores

	All	Lagged Read	No Spec Ed	Jo Sped Ed/5th Grade	All	Lagged Read	No Spec Ed	Sped Ed/5th Gra
Share undiagnosed (predicted)	10.83	1.367	1.856	-9.873				
	[23.300]	[36.289]	[25.180]	[40.237]				
Share undiagnosed(predicted)*male	-14.126	-11.457	-15.387	-11.994				
	[4.847]	[6.110]	[4.565]	[8.352]				
Share of those with ADD undiagnosed (predicted)					1.346	-2.917	0.236	-1.7
					[2.897]	[5.400]	[3.189]	[4.346]
Share of those with ADD undiagnosed(predicted)*male					-2.236	-1.92	-2.468	-1.952
					[0.682]	[0.970]	[0.694]	[1.037]
first stage residual	-0.066	1.165	-0.282	0.17	-0.043	0.323	-0.058	0.008
	[0.858]	[1.296]	[0.943]	[1.256]	[0.186]	[0.266]	[0.193]	[0.219]
first stage residual*male	-1.453	-3.754	-0.993	-1.695	-0.191	-0.82	-0.11	-0.244
	[1.497]	[1.659]	[1.406]	[1.974]	[0.267]	[0.366]	[0.288]	[0.336]
age	-0.967	2.933	-0.801	-1.147	-0.975	2.56	-0.811	-1.164
	[0.348]	[0.901]	[0.288]	[0.475]	[0.388]	[0.941]	[0.366]	[0.487]
ln(income)	0.028	0.161	0.001	-0.06	0.027	0.187	0.003	-0.052
	[0.073]	[0.127]	[0.085]	[0.123]	[0.083]	[0.147]	[0.067]	[0.108]
first grade	2.523		2.024	2.404	2.507		2.017	2.37
	[0.719]		[0.576]	[0.777]	[0.763]		[0.654]	[0.883]
third grade	4.384	-6.153	3.463	4.479	4.351	-5.679	3.472	4.467
	[1.450]	[6.431]	[1.139]	[1.642]	[1.559]	[6.018]	[1.341]	[1.790]
fifth grade	6.602	-11.773	5.229		6.554	-10.814	5.256	
	[2.189]	[6.574]	[1.709]		[2.379]	[6.004]	[2.033]	
Student in Special Ed	-0.582	-0.496			-0.585	-0.566		
	[0.300]	[0.481]			[0.344]	[0.413]		
Teacher has masters degree	0.031	-0.054	0.037	0.106	0.032	-0.078	0.032	0.086
	[0.089]	[0.102]	[0.084]	[0.107]	[0.094]	[0.111]	[0.116]	[0.122]
class size	-0.024	-0.02	-0.024	-0.031	-0.024	-0.009	-0.022	-0.02
	[0.010]	[0.014]	[0.011]	[0.017]	[0.015]	[0.021]	[0.015]	[0.027]
% Hispanic students in class	-0.902	0.106	-0.749	-0.264	-0.884	0.095	-0.723	-0.168
	[0.512]	[0.469]	[0.475]	[0.612]	[0.440]	[0.589]	[0.493]	[0.631]
% black students in class	-2.097	0.415	-1.906	-1.815	-2.077	0.375	-1.918	-1.882
	[0.356]	[0.720]	[0.361]	[0.456]	[0.378]	[0.676]	[0.368]	[0.460]
% female in class	0.476	0.147	0.3	0.165	0.443	-0.038	0.324	0.211
	[0.651]	[0.762]	[0.614]	[1.129]	[0.593]	[0.596]	[0.569]	[0.946]
Class avg. income in $10000	0.019	0.037	0.013	-0.015	0.018	0.037	0.014	-0.013
	[0.021]	[0.025]	[0.023]	[0.032]	[0.018]	[0.026]	[0.017]	[0.024]
Public School	0.66	0.926	0.876	0.495	0.709	0.961	0.825	0.289
	[0.556]	[0.910]	[0.551]	[0.762]	[0.422]	[0.577]	[0.459]	[0.656]
Catholic School	0.784	1.698	0.947	0.152	0.8	1.937	0.977	0.237
	[0.581]	[0.853]	[0.613]	[0.777]	[0.548]	[0.829]	[0.593]	[0.782]
Share Special Ed in class	0.385	0.989	1.381	1.678	0.393	1.29	1.412	1.797
	[0.409]	[0.824]	[0.659]	[1.401]	[0.460]	[0.646]	[0.603]	[1.250]
lagged reading score		0.004				0.002		
		[0.013]				[0.011]		
Observations	35000	26520	33560	25290	35000	26520	33560	25290

All regressions include individual fixed effects
Bootstrapped standard errors in brackets

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Appendix Table 1: First Stage Regressions

	Share of class with undiagnosed ADD	Share of those with ADD Currently Undiagnosed
Medicaid/SCHIP Eligibility Level	-0.00246	-0.01233
	[0.00271]	[0.01401]
Medicaid/SCHIP Eligibility Level*age	-0.00063	-0.00515
	[0.00026]	[0.00136]
age	-0.0021	-0.01499
	[0.00290]	[0.01616]
ln(income)	-0.00007	0.00195
	[0.00090]	[0.00449]
first grade	-0.00859	-0.06354
	[0.00522]	[0.02903]
third grade	-0.01442	-0.08884
	[0.01089]	[0.06073]
fifth grade	-0.02102	-0.11533
	[0.01650]	[0.09199]
Student in Special Ed	-0.00332	-0.01329
	[0.00328]	[0.01569]
Teacher has masters degree	-0.00013	-0.00714
	[0.00091]	[0.00433]
class size	0.00018	0.00344
	[0.00009]	[0.00048]
% Hispanic students in class	0.00869	0.07606
	[0.00344]	[0.01579]
% black students in class	0.0065	0.02338
	[0.00306]	[0.01619]
% female in class	-0.01574	-0.07394
	[0.00452]	[0.02279]
Class avg. income in $10000	-0.00039	-0.00136
	[0.00020]	[0.00095]
Public School	0.00946	-0.00933
	[0.00383]	[0.02038]
Catholic School	0.00567	0.05773
	[0.00434]	[0.02437]
Share Special Ed in class	0.00734	0.08257
	[0.00438]	[0.01932]
Observations	35000	35000
R-squared	0.48	0.52
All regressions include individual fixed effects		

Robust standard errors in brackets

All regressions include individual fixed effects

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Appendix Table 2 Impact of Medicaid Eligibility Status on Insurance Coverage and Diagnosis- First Stage, Reduced Form and IV Estimates

	FE-IV	FE-IV	Reduced Form	First Stage	First Stage
	Any Health Insurance	Diagnosed with ADD	Diagnosed with ADD	Eligible for Medic	le for Medicaid*age
Eligible for Medicaid/SCHIP	0.115	-0.025			
	[0.051]	[0.031]			
Eligible for Medicaid*age	-0.005	0.009			
	[0.006]	[0.004]			
Medicaid eligibility level			-0.003	0.129	-0.027
			[0.004]	[0.008]	[0.071]
Medicaid eligibility level*age			0.001	0	0.13
			[0.000]	[0.001]	[0.008]
Age	-0.002	0.005	0.004	-0.004	-0.089
	[0.004]	[0.003]	[0.003]	[0.006]	[0.050]
First grade	0.012	0.002	0.003	0.018	0.126
	[0.007]	[0.005]	[0.005]	[0.010]	[0.089]
Third grade	0.032	0.005	0.008	0.041	0.311
	[0.013]	[0.010]	[0.010]	[0.021]	[0.182]
Fifth grade	0.048	0.009	0.013	0.054	0.445
	[0.020]	[0.015]	[0.015]	[0.031]	[0.275]
Ln(income)	0.034	0.004	-0.002	-0.115	-0.959
	[0.002]	[0.002]	[0.001]	[0.002]	[0.017]
Observations	43190	43190	43190	43190	43190
Number of childid	14593	14593	14593	14593	14593

Robust standard errors in brackets

All regressions include individual fixed effects