School accountability laws and the consumption of psychostimulants [†]

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Abstract

Over the past decade, several states introduced varying degrees of accountability systems for schools, which became federal law with the passage of the No Child Left Behind Act of 2001. The intent of these laws was to improve academic performance and to make school quality more observable. Nonetheless, schools have reacted to these pressures in several different ways, some of which were not intended. We make use of the variation across states and over time in specific provisions of these accountability laws and find that accountability laws effect medical diagnoses and subsequent treatment options of school aged children. Specifically, children in states with more stringent accountability laws are more likely to be diagnosed with Attention Deficit/Hyperactivity Disorder (ADHD) and consequently prescribed psychostimulant drugs for controlling the symptoms. However, conditional on diagnosis, accountability laws do not further change the probability of receiving medication therapy.

Key words: Attention Deficit Hyperactivity Disorder, ADD/ADHD, psychostimulants, school accountability laws

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1. Introduction

Over the past decade, state level accountability systems were an important part of the education reform that aimed to unify state proficiency requirements in subjects like math and reading. Public reporting of school performance on standardized tests had an additional benefit of achieving some transparency of school quality. The presence of accountability laws varied widely from state to state, and over time until the passage of the No Child Left Behind Act (NCLB) of 2001, which required states to create an accountability system of assessments, graduation rates, and other indicators. The Act mandates that states administer high quality annual assessments to every child from grades three through eight, and must be aligned to standards consistent with nationally recognized professional and technical standards (U.S. Department of Education, 2002). The accountability provisions of the NCLB require schools to make Adequate Yearly Progress (AYP), based on student performance on these standardized tests.

The response of schools to accountability pressures is widely debated among researchers, specifically the means that schools can employ to increase the number of students who achieve proficiency on mandatory standardized tests in order to avoid sanctions if they fail to meet state targets. In an earlier review of the literature, Koretz (2002) found that the apparent gains in student academic performance may be, in some cases, illusory. For example accountability pressures generate perverse incentives to inflate scores, especially on high stakes tests that affect the school (Koretz, 2002). Specifically, studies have found sharp gains on high stakes tests accompanied by no gains on audit tests (Koretz, 1988, Koretz and Barron, 1998). In more recent studies, Neal and Schanzenbach (2007) and Reback (2008) using two separate data sets from Chicago and Texas respectively, document that schools have an incentive to improve the academic performance of students who are on the margin of passing since it is the passing rates that are being reported rather than the absolute scores. Similarly, Figlio (2006) finds that in response to accountability pressures, schools in Florida re-shaped the testing pool through selective disciplining.

Unintended consequences of accountability pressures have been shown to spill over into child health. Anderson and Butcher (2006) show that new accountability measures along with other factors such as population growth and property-tax restrictions pressure schools to raise additional funds through vending contracts and snack food sales. Such pressures translate into unhealthy school food policies and contribute to childhood obesity. Figlio and Winicki (2005) found that schools in Virginia respond to accountability pressures by offering lunches with higher caloric intake on test days to improve standardized test scores. Several studies have also shown that schools tend to respond by classifying more marginal students as disabled (Figlio and Getzler, 2006, Cullen and Reback, 2006, Jacob, 2005). Consistent with this literature, we find that school accountability laws also effect medical diagnoses and subsequent treatment options: children in states with more stringent accountability laws are more likely to be diagnosed with Attention Deficit/Hyperactivity Disorder (ADHD), and consequently, prescribed psychostimulant drugs for controlling the symptoms.[1] ADHD is a psychiatric condition which has an estimated prevalence of nearly 8% in school aged children in the U.S., and about 60% of these children are prescribed medication for the disorder (Centers for Disease Control and Prevention, 2005).

Following the passage of the NCLB, all states implemented the testing (since NCLB requires reporting of Adequate Yearly Progress by schools) and most states made report cards and ratings of schools publicly available. However, many states continued or created a system of rewards and sanctions based on whether or not students from all the different subgroups in their schools make adequate yearly progress, which is measured by how many students pass the state standardized tests. Thus, although the NCLB requires a certain minimum level of accountability to be ensured by the states, accountability standards such as the presence of school assistance, rewards and sanctions vary from state to state. Each state determines appropriate levels of proficiency for its students and can choose to reward or sanction schools based on their performance.

In this paper we show that accountability pressures affect the probability of diagnosis and medication for ADHD. We exploit the variation in specific provisions of state laws regarding accountability that vary by state and years and, link this information to two unique data sets on medication and diagnosis. The first data set provides aggregate measures of the consumption of all psychostimulant drugs by state and year between 1999 and 2003, while the second data set is nationally representative data of all school aged children for 2003, and includes information on individual and family characteristics as well as the children's health status, including if they are ADHD and on medication for it.

With the first data set, we use a difference-in-difference model and take advantage of both, a between-state variation in accountability laws, as well as variation over time to show how changes in school pressures to improve academic performance effect overall psychostimulant consumption. In the second data set, we supplement our analysis of the U.S. per-capita consumption level with an analysis of individual, student-level diagnoses of ADHD and psychostimulant consumption for children enrolled in public schools. This individual micro-level data allows us to control for child and family characteristics to estimate the marginal impact of accountability laws on the probability of ADHD diagnosis and medication therapy. Additionally, using the micro-level data we construct a falsification test for the effect of these laws: it is possible that accountability laws, which are at the state level, are correlated with other unobserved state level factors that are responsible for diagnosis

[1]Psychostimulants are the most commonly prescribed drugs for the treatment of ADHD, and include Schedule II drugs such as Methyplhenidates (e.g Ritalin, Concerta), Mixed Amphatamine Salts (e.g Adderall) and Dextroamphatamines (e.g Dexedrine). Other molecules used for treatment of ADHD include Pemoline (Cylert) which is Schedule IV drug and Atamoxatine (Stratera) which is not a stimulant drug.

of ADHD (and not the laws per se). Hence, we repeat the analysis on children enrolled in private schools, a group that is not subject to the accountability laws, but have otherwise similar risk factors associated with being diagnosed with ADHD. For this subgroup we find that the state laws do not the change the probability of diagnosis, lending credence to our claim that the accountability laws are not just reflecting the effect of other state level unobserved factors that effect the diagnosis of ADHD.

Our results indicate that provisions of assistance, rewards or sanctions are all associated with a statistically significant increase in aggregate pschostimulant consumption but only assistance is statistically significant conditional on the other two laws. Presence of a law about assistance increase the aggregate consumption by about 2.4%. An accountability index that measures the overall strictness of the accountability laws (as a sum of the number of laws that are present, ranging from 0 for no accountability laws to 3 for all three present) shows that every additional law increases consumption by about 1.8%. Further, these provisions increase the probability of being diagnosed with ADHD for an individual school aged child by .020 and .012 for assistance and rewards respectively, while the provision for imposing sanctions on poor performing schools is not significant. Similarly, the marginal effect of the accountability index is .006. Finally, the accountability laws do not change the probability of receiving medication therapy conditional on being diagnosed with ADHD. Thus, medication therapy and overall consumption of stimulants increases because more children are diagnosed with ADHD rather than because more children who are ADHD are prescribed medication therapy. According to our simulations, about 936,660 *fewer* public school children would be diagnosed with ADHD when no accountability laws are present versus when all three laws are present.

It is important to note that the potential increase in ADHD diagnosis and psychostimulant consumption rates that follows a hike in school accountability pressures is not necessarily undesirable. On one hand, some schools may be "gaming the system" by inappropriately labeling marginal students as ADHD to provide them with accommodations as well as to reshape the testing pool. On the other hand, stricter accountability leads to more ADHD students receiving the appropriate diagnosis, academic accommodations and efficacious medical treatment that improves their academic performance, as well as of their peers. While physician decisions on ADHD cases are certainly influenced by input from school personal (as we later argue), our study provides a possible opportunity for interpreting whether the behavioral consequences of accountability have been positive or negative along this one dimension. This can be important because many children with ADHD, if untreated, continue to exhibit symptoms of the disorder into adulthood, where such symptoms impair activities of daily living, educational achievement and productivity (Murphy and Barkley, 1996, Secnik et al., 2005, Biederman and Faraone, 2006). For example, Biederman and Faraone

(2006) found that subjects in the ADHD group are less likely to pursue education beyond some high school or to hold a full time job, and computed loss of workforce productivity associated with ADHD between $67 billion and $116 billion. Therefore, early identification and treatment may alleviate some of these workforce losses.

The link between accountability pressures and ADHD diagnoses and medication therapy requires both, the incentives as well as the ability, of school personnel to influence medical decision making. In the next section, we argue that schools do have both the incentive and the ability to influence the diagnosis of ADHD. Section 3 describes the provisions of the state level accountability laws that we use in our analysis and provides details of our data. This section also outlines our estimation strategy. The fourth section provides descriptive statistics as well as the main results. This is followed by a brief summary and conclusions section.

2. Role of School Personnel in ADHD Diagnosis

Schools may have strong incentives to label a child as ADHD for several reasons. First, ADHD is a disorder associated with significant impairments that commonly continue into adulthood, including poorer performance and earlier exit from school (Mannuzza et al., 1997). Once a child is diagnosed, s/he may receive psychostimulant and other treatments. The psychostimulant treatments have been established to be efficacious, resulting in improved classroom behavior as well as some improvements in academic achievement: Carlson et al. (1992) found that both methylphenidates and behavior modification alone significantly improved children's classroom behavior, but only methylphenidates improved children's academic productivity and accuracy. Evans and Pelham (1991) in a double-blind, placebo-controlled assessment found significant effects of psychostimulants on quiz and test performance, observations of attention and behavior during lectures, teacher ratings, as well as accuracy on assignments completed during study hall. Similarly, A Multimodal Treatment Study of Children with ADHD used a randomized treatment design and followed a cohort of 579 ADHD children over 14 months. The study found a significant reduction in symptoms over time and children who received psychostimulant treatment showed significantly greater improvement than those given intensive behavioral treatment and community care (MTA Cooperative Group et al., 1999a,b). More recently, a comprehensive review of the current literature by The American Academy of Pediatrics' Committee on Quality Improvement, Subcommittee on Attention-Deficit/Hyperactivity Disorder found that current empirical evidence strongly supports the use of stimulant medications for treating the core symptoms of children with ADHD with significant effects on measures of attention, distractibility, and impulsivity and observable social and classroom behavior. Some modest effects were also found for academic achievement with effect sizes of 0.19-0.47 with mean of 0.34 (Brown et al., 2005). Finally, Barbaresi et al. (2006) in a population-based study found that on average psychostimulant treatment was modestly correlated with improved reading achievement scores (ρ = .15, p = .012), that both treatment with psychostimulants and longer duration of medication were associated with decreased absenteeism, and that children with ADHD who were treated with stimulants were 1.8 times less likely to be retained a grade than children with ADHD who were not treated (however, they found no association between psychostimulant treatment and school dropout rates).

Second, in addition to the improvements in behavior and academic achievement of the child with ADHD, treatment may also improve the achievement of other children in the classroom via peer effects. Aizer (2008) reports that children with non-diagnosed ADHD lower the reading test scores of non-ADHD classmates (if 8.5 percent of the class have undiagnosed ADHD test scores will be 2 points or 20 percent of a standard deviation, lower) but once these children are diagnosed, no such externalities are observed. Moreover, ADHD students put more stress on teachers as measured by Index of Teaching Stress (Greene et al., 2002) and psychostimulant treatment has been shown to improve teacher's ratings of children's ADHD symptoms (Pelham et al., 2000).

Third, ADHD is a disability that is recognized by the Individuals with Disabilities in Education Act (IDEA). Thus, all ADHD students are entitled to academic accommodations, although accommodations under IDEA vary across states.[2] Additionally, some states report results on state standardized tests for students with learning disabilities separately.[3] Identifying a previously undiagnosed child with ADHD could improve the academic performance of students in both pools, students with learning disabilities (since, as previously noted, psychostimulant treatments have been established to be efficacious for children with ADHD) as well as for the general student population since ADHD kids do worse than typical peers. Therefore, ensuring psychostimulant treatment to ADHD students serves as an effective strategy that schools and teachers may employ to meet state proficiency requirements.

Although schools and teachers are not physicians and cannot diagnose or prescribe drugs, they have a strong influence on the medical decision making process. Since there are no laboratory tests that can be performed to diagnose ADHD and other such learning problems, the diagnoses of ADHD have always been controversial. To meet the diagnostic criteria for ADHD at least six of the eighteen known ADHD symptoms must be met (American Psychiatric Association, 1994). Some of

[2]Under the policy change to IDEA in 1990, the Department of Education issued a policy clarification memorandum in 1991 stating that schools not only had to provide special services and accommodations for children with sufficiently severe ADHD, they had to evaluate all children suspected by their parents and local education agencies of having the disorder (Aleman, 1991). Currently, the U.S. Department of Education states that children diagnosed with ADHD are eligible for special education services and are categorized under "Other Health Impaired" (Sec. 300.7) group of disabilities. Also, the new regulations implementing the IDEA Amendments of 1997 (issued March 12, 1999) for the first time explicitly incorporate ADHD within the definition of "Other Health Impaired".

[3]For instance, the Adequate Yearly Progress (AYP) requirements of NCLB also require schools to meet benchmarks for distinct sub-populations, one of which is students with disabilities.

the symptoms refer directly to school behavior, such as "often leaves seat in classroom or in other situations in which remaining seated is expected". Parents and physicians often rely on schools and teachers since most of ADHD symptoms are exhibited almost exclusively in classroom settings. Previous studies show that schools and school teachers play an important role in identifying potential ADHD students and motivating parents to seek treatment. Sax and Kautz (2003) report that in 52.4% of the cases, ADHD diagnosis was first suggested by a child's teacher or other school personnel. Arcia et al. (2004) find that school reports of behavioral difficulties and direct school referrals for assessment and treatment of disruptive behavioral problems were major determinants of entry into services. In addition, pressures from schools such as insistent (e.g. daily) calls from teachers or administrative staff and suggestions to consult a pediatrician or psychiatrist were final motivators for treatment-seeking in 17.7% of interviewed mothers. Similarly, Schneider and Eisenberg (2006) found that teacher's characteristics significantly affect the probability of an ADHD diagnosis.

3. Data Description and Empirical Strategy

Our data come from three primary sources: (1) Data on timing of school accountability laws (between 1999 and 2003) at the state level available from the Quality Counts data published on the www.edweek.org website, (2) Data on aggregate consumption of all ADHD related drugs by geographic areas provided by NDCHealth and covers the periods 1999 through 2003 and, (3) The National Survey of Children's Health, a nationally representative sample of individual data on children aged 0-17 collected in 2003. This data set also indicates if these children are diagnosed with ADHD and whether they are currently on any medication for treating ADHD symptoms. We linked the first data set on state level accountability laws to each of the two latter data sets.

Data on state accountability laws for years 1999 through 2003 is based on Education Week Research Center's annual state policy survey. For our analysis, we use five specific dimensions of the school accountability laws. These are as follows:

(1) ReportCard: State has a report card for each of its schools?
(2) Ratings: State rates schools or identifies low-performing schools?
(3) Rewards: State provides monetary rewards to successful schools?
(4) Assistance: State assists schools it names low-performing?
(5) Sanctions: State authorized to close/takeover/reconstitute failing schools?

Since the passage of the No Child Left Behind Act all states have ratcheted up their accountability efforts, though certain areas have seen more movement than others. By 2004, all states provided school report cards (although only 40 states did so in 1999), which commonly include student test scores broken down by race, family income, limited English proficiency, and disability. On the basis of these report cards, states issue public ratings of schools that identify low-performing and, in some states the highest-performing schools. Assistance to low-performing schools usually comes in the form of expert advice and a school-improvement plan. Based on ratings under the state accountability system, states may choose to offer monetary rewards to successful schools. Some states also have time limits on how long a school can be identified as low-performing before the state must take action in a form of sanctions. States have the legislative authority to withhold funds, close, take over, or "reconstitute" a failing school as a charter school. Such actions mean that the school is closed and then reopened under new management and with substantially different staff. Note that very few states have actually ever sanctioned schools. While all states now provide technical help and impose sanctions for Title I schools that fail to make adequate yearly progress, as required under the NCLB, states receive credit in this study only if their technical assistance, sanctions, and rewards apply to all public schools in the state, not just Title I schools. In 2004, 36 states made technical assistance available to all low-performing schools. Twenty-nine applied sanctions to such schools. Seventeen states offered rewards to high-performing or improved schools.

We linked the state accountability laws data set with data on the consumption of psychostimulant drugs by year and geographic areas. The consumption data is derived from NDCHealth's proprietary Source Territory Manager ® data files for the calendar years listed above which report the total number of pills sold at retail centers by strength (in milligrams) for various drugs at the 5-digit zip code level within the entire continental U.S. The drugs reported in this data set span across a number of different drugs used for the treatment of ADHD which were in the market during the study period. Thus, for instance, the data set includes observations on drugs that were already on the market at the beginning of the study period (e.g. Ritalin and Ritalin-SR) as well as those that were introduced during the study period (e.g. Ritalin-LA which was introduced in 2002). The drugs that we included for our analysis were all brand names and generics that contained either Methylphenidate HCL (e.g. Ritalin, Concerta, Metadate, Methylin), Mixed Amphetamine Salts (e.g. Adderall, Adderall XR), Dextroamphatamines (e.g. Dextrostat, Dexedrine), Dexmethylphenidate (e.g. Focalin), and Methamphetamine (e.g. Desoxyn), and were prescribed for treating ADHD. For each drug, we first aggregated the data by strength within each zip code and then aggregated it up to the state level.

We validated NDCHealth's data by comparing the reported quantity sold (in gms) in 1999 with the Drug Enforcement Agency's (DEA) ARCOS data for 1999, which records the total amount shipped to each area. We found the correlation between these measures from two different data sources to be very high (ranging from 0.65 to 0.9 depending on whether we compared the overall rates or individually for all counties within a state or census division) and thus provides us with reasonable confidence in our data. However, one shortcoming of this data set is that it does not tell us who is consuming these drugs. Clearly, not all of these drugs are consumed by children. An auxiliary data set obtained from the Department of Justice of California (which maintains California's data on prescriptions of Schedule II drugs due to the State's Monitoring Law) indicates that in 2001 about 67% of all psychostimulants were consumed by individuals aged 20 or less. While this figure is likely to be different across states (and somewhat over the years as well), nonetheless, as long as this percentage does not vary too much across states, we can use this aggregate data in out reduced form analysis.

In our reduced form regression analysis we use the *timing* of the state laws to identify whether the adoption of accountability state laws leads to greater consumption of psychostimulants. We use variation between states and over time as accountability standards change to identify the impact of each accountability tool on psychostimulant use. Specifically, using state and year fixed effects, we regress the log of total quantity (not the rate as computed above) on a set of dummy variables for accountability laws and other state level control variables and estimate regressions of the form

$$lnQ_{it} = \beta_0 + \alpha_j L_{jit} + \beta X_{it} + \sum_{i}^{48} s_i S_i + \sum_{t}^{5} \tau_t T_t + u_{it} \tag{1}$$

where L_{jit} is a dummy indicator equal to one if the jth accountability law is in effect in state i in year t, S_i and T_t are state and year fixed effects, X_{it} is a vector of other state-year covariates, and lnQ_{it} is the log of total quantity consumed in state i and year t. Thus, we are implicity assuming that after including the state and year fixed effects in the equation above, L_{jit} and u_{it} are not correlated.

In addition to the aggregate data described above, we also use individual level data which identifies school aged children who have been diagnosed with ADHD, and among those diagnosed with ADHD, which students are currently on medication therapy specifically for ADHD. The National Survey of Children's Health (NSCH), collected in 2003-04, is a nationally representative individual level data on 102,353 children from 50 states and District of Columbia. Since the state in which the child resides is known, we link this data to the state accountability laws for 2003 (for Rewards, Assistance and Sanctions only since the other two laws were in effect in all states by 2003), and after controlling for individual characteristics, assess the impact of these laws on the diagnosis of ADHD and on medication therapy for a child.

ADHD is not a discrete medical condition, though the diagnosis is discrete, and hence we investigate the impact of accountability laws on ADHD diagnosis and medication therapy via the use of a latent variables model. Since medication can only be prescribed if a child is first diagnosed with ADHD, we estimate a sequential probits model of the form $D_i = 1$ if $D_i^* > 0$ and $(M_i|D_i = 1) = 1$ if $M_i^* >$

0 where

$$D_i^* = \beta_1 L_i + \sum_{j=2}^{k} \beta_j X_{ji} - \epsilon_{1i} \tag{2a}$$

$$M_i^* = \alpha_1 L_i + \alpha_2 \tilde{D}_i + \alpha_3 L_i \tilde{D}_i + \sum_{j=4}^{k} \alpha_j X_{ji} - \epsilon_{2i} \tag{2b}$$

and $\tilde{D}_i = Pr(D_i^* > 0)$.

In the first equation above, D_i^* is the *perceived* severity of ADHD of child i, as perceived by a physician, and is a function of individual characteristics of the form $\sum_{j=2}^{k} \beta_j X_{ji}$ of the ith child. While the diagnosis of ADHD is given solely by the physician based on her/his own observation of the child, in turn the physician also relies on symptoms and behavior as reported by parents and teachers. Since in the presence of accountability laws, the latter group *may* have an incentive to have a child diagnosed with ADHD, they can influence the physician's perception of the severity of ADHD (via the reports of classroom behavior and symptoms) and hence we also specify D_i^* as a function of L_i, an indicator variable equal to one if a specific school accountability law (or a vector of such laws) is in effect in the state of student i. If $\beta_1 = 0$, then accountability laws do not influence the perception of severity of ADHD and consequently the decision to diagnose a child as ADHD.

In the second equation, M_i^* is the *expected* efficacy of medicating a child and is a function of his/her characteristics and of the probability that the child is diagnosed with ADHD. The higher the probability of diagnosis, the greater is the underlying severity of ADHD, and hence greater the efficacy of medicating a child. Thus, we expect $\alpha_2 > 0$. Once again, the final decision to start medication therapy is reached jointly only by the physician and parents, but the decision process is not without input from the teachers (at least indirectly) and hence the expected efficacy of the medication therapy may also be a function of school accountability laws. We test for this by letting M_i^* be a function of L_i and of the interaction of L_i with $\tilde{D}_i$.

Since the model specified above is a sequential probit (a person can be medicated only after they have been diagnosed) it is internally consistent and the parameters are identifiable.[4] Thus, our estimation strategy relies on two parts. In the first part, we use the entire sample and estimate the first equation via a probit and where the coefficient on the indicator variable tells us if the accountability law has an impact on the probability of receiving an ADHD diagnosis. Next, we use the coefficients from this probit to compute $\widehat{\tilde{D}}_i = \Phi(X, L; \widehat{\beta})$ and use these in the probit estimation of the second equation which is estimated on the sub-sample of children diagnosed with ADHD. The coefficients α_1 and α_3 identify the impact of the accountability laws on the probability of receiving medication therapy, conditional on ADHD diagnosis.

[4]See Maddala (1983) pp. 123 for a similar model (eqn. 5.51).

4. ACCOUNTABILITY LAWS, ADHD DIAGNOSIS AND MEDICATION

4.1. **Aggregate Consumption.** Between 1999 and 2003, the number of states that adopted these laws grew substantially. For instance, in 1999 the number of states that had a law about issuing report cards was 38, but by 2003 all states had adopted such a law. However, in 1999 the number of states that had a law about imposing sanctions on poor performing schools was 18, but by 2003 the number increased to 26. The number of states adopting such laws did not increase monotonically over the years. For instance, states that reward successful schools grew from 13 in 1999 to 20 in 2000 and then slowly declined back to 16 by 2003. Over the same years, the average consumption rate across states grew from approximately 4,750 gms/100K Children (age $\leq$ 20) to about 10,300 gms/100K Children. See Table 1 for a summary of diffusion of these state laws and mean consumption rate by year.[5]

TABLE 1. Summary of State Laws and Consumption Rates†

	Summary of State Laws					Summary of Consumption Rate††			
Year	R-Cards	Ratings	Rewards	Assistance	Sanctions	Mean	Min	Max	Stdev
1999	38	21	13	20	18	4,746	2,468	7,634	1,005
2000	43	27	20	27	14	5,453	2,902	8,675	1,164
2001	41	29	18	28	20	6,444	3,307	10,406	1,480
2002	46	30	17	28	23	8,012	4,119	12,802	1,854
2003	48	49	16	34	26	10,331	5,274	16,531	2,303

†Data from 48 states and D.C. (Alaska and Hawaii not included)
††Consumption Rate computed as 70% of total consumption (in gms) divided by 100,000 Population Age $\leq$ 20

There also appears to be some correlation between state level consumption rates and accountability laws. For instance, the five-year average consumption rate in states that do not have a law about assisting poor performing schools is 6,585 gms/100K Children, while the average is 7,310 gms/100K Children in states where such a law exists (see Table 2). Similarly, the five-year average for states without a law about imposing sanctions on failing schools is 6,844 gms/100K Children while in states when such a law is present the average consumption rate is 7,204 gms/100K Children. Further, the five-year average consumption rate is always higher in states where an accountability law is present except in the case of a law about rewarding successful schools. However, the difference in five-year averages is somewhat misleading in terms of correlations since the number of states where a specific law is present is not constant over these years (as can be seen in Table 1). In fact, if we look at the year-by-year difference in averages between states that have a specific accountability law versus

[5] In the regression analysis, we use the log of total quantity. However, for the purpose of descriptive statistics *only*, we compute and tabulate consumption rate among children by state-year as equal to .7× (total consumption in state-year) ÷ (number of persons age $\leq$ 20). The 70% figure is based on the an auxiliary data set by DOJ California that suggests that about 70% of all psychostimulant drugs are consumed by individuals age 20 or less.

those that do not (see Table 2), no clear pattern emerges that would indicate presence of any strong correlation.

TABLE 2. Mean Consumption Rate by State Law Status

	STATES THAT HAVE NOT ADOPTED THE LAW					STATES THAT HAVE ADOPTED THE LAW				
Year	R-Cards	Rate	Rewards	Assist	Sanction	R-Cards	Rate	Rewards	Assist	Sanction
1999	4,717	4,864	4,847	4,778	4,616	4,695	4,489	4,303	4,590	4,838
2000	5,378	5,398	5,466	5,398	5,439	5,406	5,407	5,315	5,407	5,318
2001	6,823	6,344	6,549	6,463	6,397	6,370	6,512	6,262	6,429	6,512
2002	8,640	7,970	8,098	7,671	8,145	7,971	8,040	7,851	8,269	7,862
2003	13,844	-	10,342	10,273	10,921	10,258	10,331	10,308	10,356	9,809
All Years	6,238	6,011	7,083	6,585	6,844	7,088	7,542	6,826	7,310	7,204

Looking at these aggregate statistics one could even make the case that it is precisely the states with a greater propensity to consume psychostimulants that pass school accountability laws. While this is certainly possible, we do not think that the passage of school accountability laws is endogenous to the consumption of psychostimulants. Thus, using aggregate state level data on total consumption of psychostimulants for the years 1999-2003, we estimated Equation 1 separately for each of the five accountability laws. The regressions includes a dummy variable indicating if a specific accountability law is in effect. Each regression also includes state and year dummies as well as (log of) total population and percent of school aged population. The regression coefficients on the law variables are given in columns marked (1) through (7) of Table 3. To account for arbitrary correlation of the error terms within a state over time, standard errors are clustered by state.

Columns (1) and (2) indicate that, neither the law about states issuing report cards, nor the law about a state rating its schools had any significant impact on the consumption rates. While this could be because these two laws truly had no impact on consumption rates, it is more likely that our data is not adequate for identifying any effect of these laws. Specifically, we have a short panel (5 years, 48 states and D.C. not included) and there is not enough variation over time and states in these two laws: In 1999, 38 states had already adopted a law about issuing report cards and the number had grown to only 41 by 2001. With the passage of the No Child Left Behind Act, all remaining states more or less simultaneously adopted the report cards and ratings law (by 2003, virtually all states had adopted these two laws, see Table 1) such that the variation in consumption rates across states and over time can not be separated from the adoption of these laws. By comparison, the other three accountability laws (rewards, assistance and sanctions) were not part of the No Child Left Behind Act and as such the adoption of these laws vary by states and years over the entire panel. Thus, if these laws had any impact on the consumption rates, we should be able to pick up their effect with our identifying strategy.

TABLE 3. Regression Log Quantity on State Accountability Laws

Dependent Var: Log Quantity (in gms) of all ADHD drugs w/ Amphetamine or Methylphenidate

(N = 240 All regressions)	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Report Cards Law	0.888 (0.317)	0.0025 (0.015)							
Rates Law	0.638 (0.482)		0.019 (0.013)						
Assistance Law	0.567 (0.497)			0.034^a (0.011)			0.030^b (0.012)	0.024^c (0.014)	
Rewards Law	0.350 (0.478)				0.022^c (0.012)		0.015 (0.012)	0.015 (0.012)	
Sanctions Law	0.417 (0.494)					0.024^c (0.013)		0.014 (0.014)	
Accountability Index†	1.333 (1.134)								0.018^a (0.0052)
Year‡ 2000	0.200 (0.401)	0.14^a (0.013)	0.14^a (0.013)	0.13^a (0.013)	0.13^a (0.013)	0.14^a (0.013)	0.13^a (0.013)	0.13^a (0.013)	0.13^a (0.012)
Year‡ 2001	0.200 (0.401)	0.27^a (0.017)	0.27^a (0.017)	0.27^a (0.017)	0.27^a (0.016)	0.27^a (0.016)	0.26^a (0.016)	0.26^a (0.016)	0.27^a (0.015)
Year‡ 2002	0.200 (0.401)	0.45^a (0.021)	0.45^a (0.021)	0.44^a (0.021)	0.44^a (0.020)	0.45^a (0.020)	0.44^a (0.021)	0.44^a (0.021)	0.44^a (0.020)
Year‡ 2003	0.200 (0.401)	0.54^a (0.025)	0.53^a (0.027)	0.53^a (0.026)	0.53^a (0.024)	0.53^a (0.025)	0.52^a (0.026)	0.52^a (0.025)	0.53^a (0.024)
Ln Population	15.122 (0.992)	-0.87^a (0.30)	-0.88^a (0.29)	-0.88^a (0.29)	-0.82^a (0.30)	-0.91^a (0.28)	-0.84^a (0.29)	-0.87^a (0.28)	-0.86^a (0.28)
% Age 5-19	21.524 (1.293)	0.040^b (0.016)	0.043^b (0.016)	0.036^b (0.016)	0.040^b (0.016)	0.038^b (0.016)	0.037^b (0.016)	0.037^b (0.016)	0.037^b (0.016)

Note 1: All regressions include state and year dummies. The sample consists of 48 States (Hawaii and Alaska excluded) and does not include D.C.
Note 2: a, b, c are significance levels at 1,5 and 10% respectively, and clustered (by state) standard errors are in parenthesis.
† Accountability index is the sum of dummy variables for Assistance, Sanctions and Rewards.

Columns (3) to (5) indicate that laws about assistance, sanctions and rewards have a statistically significant impact on the consumption rates. Per capita psychostimulant consumption increased by 3.4% for states with assistance, and by 2.2% and 2.4% for states with sanctions or rewards for poorly rated schools. Next, to access the cumulative impact of these three laws on consumption rates, in columns (6) and (7) we included, first just two laws and then all three simultaneously. The coefficients on all three decrease in magnitude (compare these magnitudes to those in columns (3) to (5)) and the coefficient on sanctions is no longer significant. Thus, conditional on the presence of the other two laws, while assistance has a statistically significant effect on the consumption rates, this does not appear to be so for rewards or sanctions. We further verified the cumulative effect of these three laws by constructing a simple accountability index as the sum of the dummy variables (where the sum ranges from zero to three) and using that in the regression analysis. The results are given in column (8) and show that a one point increase in the index is associated with a 1.8% increase in the consumption.[6] Thus, having two or three of these laws on the books is associated with a significant increase in psychostimulant use per capita relative to states that enforce none or just one of these three laws.

Robustness. In the preceding regressions, our identifying strategy was to make use of the variation in the timing of adoption of laws by states. Further, we have relied on state and year fixed effects (as well as the size of the relevant population) to capture the effect of all remaining variables that are either common to all states and changing over time or common to all time periods but are state specific. However, state specific factors that are changing over time are not controlled for in the regressions and are still in the error term. If these variables are correlated with the accountability laws, then the estimated coefficients on the state accountability laws are biased (and inconsistent).[7] To check if this is true, i.e., if the unobserved state specific factors that are changing over time are correlated with the accountability laws, we estimated additional fixed effects regressions but this time included a series of covariates specific to states and changing over time, i.e., for each of the regressions above, we included a vector of variables X_{it}. Specifically, we included log of total population, percent of African-American population, percent of other minorities, percent of population aged 5 to 19, log of children enrolled in special education programs, log of child population participating in school lunch programs, student teacher ratios, unemployment rates, per capita income, percent uninsured and log of total medicaid compensation in the state. Adding in these covariates did not change the coefficients on the state law dummies appreciably (in magnitude) in any of the regressions nor did the level of significance ever change. The results from these additional regressions are given in the appendix (see Table 6). While this is far from a strong statistical evidence in support of no omitted variables *bias*, it does increase confidence in our fixed

[6]We also experimented with non-linear effects in the accountability index. For instance, we constructed two alternative dummy variables indicating if there were two or three out of three laws in effect (the comparison group was zero or one law in effect) and found that presence of any two such laws is associated with 2.2% increase in the consumption while having all three laws in effect is associated with a 5.3% increase in the consumption rates. Similarly, we also estimated the model with zero and one law separated out into two separate categories. The results were similar though somewhat weaker since the panel is not large enough to allow such refined division of observations into that many cells.

[7]Two common sources of such endogeneity are omitted variables and simultaneity (or reverse causality). We do not think that simultaneity is a realistic concern since that would require that state legislators are passing accountability laws at specific points in time in response to consumption of ADHD drugs. However, omitted variables bias is still possible. The standard method to correct for such a bias would be through the use of instrumental variables (or to check for it via the usual Hausman test). We do not have any valid instruments (i.e., uncorrelated with consumption rates) that also correctly predict the timing of accountability laws by state (i.e. are also relevant).

effects approach to the extent that if these other unobserved omitted variables are similar to the ones that were included, they are not necessarily correlated with the state law dummies. In fact, the only time we see an appreciable change in the magnitudes of the law dummies is if we do not include any state dummies. In that case, the law dummies hover around 7% to 9% depending on which state level covariates are included in the regression. This gives us some confidence that any state-time covariates that are omitted from Equation 1 and which may be correlated with the timing of the law are absorbed in the state and year dummies. Thus, including state and year dummies reduces or eliminates omitted variables bias.

One shortcoming of the above analysis is that we actually do not know what fraction of these psychostimulant sales were for school aged children. As long as either the fraction of total sales to children is the same across states, or if it is different, then it is not systematically correlated with the accountability laws, the above analysis is still valid (since then it is absorbed by the state dummy variables). Thus, the analysis above assumes that the differences in the fraction of sales to children across states is not correlated with the accountability laws. However, no such assumption in needed in the individual level analysis in the next section.

4.2. **Probability of Diagnosis and Medication Therapy.**

Sample. The medical and epidemiological literature lists several risk factors associated with the diagnosis of ADHD and drug therapy, including (but not limited to) age, gender, race, ethnicity, income, insurance, parent's education and family structure. In our estimation of the probits specified in Equation 2, we include all these variables in the vector X_{ji}. Additionally, we also include some of the state level variables used in the aggregate analysis (percentage of population aged 5 to 19, log of children enrolled in special education programs, log of child population participating in school lunch programs, and student teacher ratios). For our analysis, we restricted the sample to school-aged children (ages 5 to 17)who are enrolled in public schools (those in private schools are not subject to the accountability laws). The final sample, and for which the information on the covariates in not missing, consists of 49,527 children. Among these sample children, 4,715 (9.52%) were diagnosed with ADHD while the remaining 44,812 (90.48%) were not. Further, of the 4,715 children with ADHD, medication therapy status is known for all but 14 children. Thus, of the 4,701 children, 2,824 (60.1%) were on ADHD medication therapy. Data for selected covariates is summarized in Table 4.

Descriptive Statistics. The NSCH data set is based on a complex survey design and provides variables that identify stratas (states) and the post-stratification probability of including a child in the sample (weights). Thus, from here onwards, we only report results that weight the observations appropriately and where standard errors are always clustered by states. While only 9.52% of all children in our sample are diagnosed with ADHD, 85.5% of them reside in states where the Assistance Law was in effect. By comparison, 82.9% of those not diagnosed with ADHD reside in similar states. Similarly, 37.4% and 73.2% of children diagnosed with ADHD live in states with Rewards and Sanction laws but among those who are not diagnosed with ADHD, 32.6% and 72.5% live in states with similar laws. In each of these three cases, a slightly higher percentage of children diagnosed with ADHD live in states with these three accountability laws compared to the percentage of children not diagnosed with ADHD. Of those diagnosed with ADHD, 60.07% are on drug therapy for ADHD. However, no clear pattern on medication status by state law exists for these children: a smaller fraction of children on medication therapy live in states that have Assistance and Sanctions laws (84.5% and 71.8% respectively) compared to the percentage of children not on medication therapy (86.8% and 75.0%), but a slightly larger fraction of children on medication therapy reside in states that have the Rewards law in effect compared to the fraction of children not on medication therapy (38.1% vs. 36.5%).

The descriptive statistics for all the remaining covariates are provided in the appendix, but a few typical 'risk factors' associated with ADHD diagnosis and medication therapy are summarized in Table 4. Observe that children diagnosed with ADHD are slightly older than their counterparts while those on medication (conditional on being diagnosed) are younger than those not on medication. Similarly, compared to females, males are significantly more likely to be diagnosed with ADHD (among those diagnosed, 72.9% are males while only 27.1% are females) as well as be on medication for ADHD (among those medicated, 73.3% are males while only 26.7% are females). However, while the conditional distributions of gender, conditional on ADHD = Yes/No are very different, the conditional distributions of gender, conditional on Medication = Yes/No (and ADHD=yes) are very similar (note that the mass of the conditional distributions on the last two columns under medication status for gender are very similar but those under diagnosis are very different). Thus the conditional distribution of gender, conditional on medication status, appears to be orthogonal to the medication and suggests that while gender is a significant risk factor for diagnosis, there is little difference in medication therapy by gender among those diagnosed. Finally, both race and ethnicity appear to be significant risk factors for the diagnosis of ADHD (the conditional distributions by ADHD status are quite different): compared to White children, African Americans and others are less likely to be diagnosed with ADHD. Similar differences in race/ethnicity conditional distributions appear by medication status, but since it is also conditioned on ADHD status equal to yes, it is not clear if the differences in conditional distributions of race/ethnicity by medication status are merely a reflection of the difference already noted in diagnosis status.

Probability of Diagnosis. While these descriptive statistics are revealing, they do not provide the full story of how these laws affect the probability of diagnosis and medication for children who are

Table 4. Proportion of Children in States with Accountability Laws by ADHD and Medication Status

	ADHD? (N=49,527)		Medication? (N=4,701)| ADHD=Yes	
	Yes(9.52%)	No(90.48%)	Yes(60.07%)	No(39.93%)
Assistance Law	0.855	0.829	0.845	0.868
(1/0: 1 if State Law in effect)	(0.053)	(0.061)	(0.058)	(0.048)
Rewards Law	0.374	0.326	0.381	0.365
(1/0: 1 if State Law in effect)	(0.092)	(0.087)	(0.093)	(0.095)
Sanctions Law	0.732	0.725	0.718	0.750
(1/0: 1 if State Law in effect)	(0.073)	(0.075)	(0.077)	(0.071)
AI: Accountability Index	1.962	1.880	1.945	1.984
(Sum of the three laws)	(0.140)	(0.137)	(0.142)	(0.142)
Age	11.911	11.542	11.362	12.665
	(0.072)	(0.033)	(0.095)	(0.096)
Gender	0.729	0.492	0.733	0.723
(1/0: 1 if Male)	(0.009)	(0.004)	(0.012)	(0.016)
Gender	0.271	0.508	0.267	0.277
(1/0: 1 if Female)	(.009)	(.004)	(0.012)	(0.016)
Race	0.790	0.747	0.812	0.758
(1/0: 1 if White)	(0.013)	(0.150)	(0.122)	(0.019)
Race	0.143	0.166	0.125	0.168
(1/0: 1 if African American)	(0.018)	(0.018)	(0.016)	(0.027)
Race	0.067	0.087	0.063	0.074
(1/0: 1 if Other)	(0.010)	(0.017)	(0.008)	(0.015)
Ethnicity	0.053	0.089	0.042	0.068
(1/0: 1 if Hispanic)	(0.012)	(0.022)	(0.008)	(0.023)

The table displays the mean of the dummy variable and the clustered standard error in parenthesis

ADHD. Thus, we estimated the probability of diagnosis and subsequent medication per specification given in Equation 2. Columns (1) through (6) of Table 5 provide the estimated coefficients on accountability laws of the probability of being diagnosed with ADHD. Note that the table displays only selected coefficients (the full set of results is given in the appendix in Table 7).

In the first three specifications, we included the three accountability laws one at a time in the probit for ADHD. Column (1) shows that the coefficient on the assistance law is .11 and is statistically significant at the 1% level. The marginal effect of the law on the probability of being diagnosed is .0153 at the sample mean with the associated p-value less than 0.000 (the mean of the marginal was also computed and was .0154). When we replace the assistance law with the rewards law, the coefficient is slightly smaller (.077) and is significant at the 5% level. The marginal effect of the law at the sample mean is .012 with a p-value of .048 while the mean of the marginals is

Table 5. Probability of ADHD Diagnosis and of Medication for ADHD

Selected coefficients shown. Detailed results given in the appendix.

	Pr(ADHD=1)						Pr(Meds=1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assistance Law	0.11^a							
(1/0: 1 if State Law in effect)	(0.024)							
Rewards Law		0.077^b						
(1/0: 1 if State Law in effect)		(0.038)						
Sanctions Law			0.027					
(1/0: 1 if State Law in effect)			(0.036)					
AI: Accountability Index				0.045^a	-0.014	0.047^c	0.035^b	0.084
(Sum of the three laws)				(0.014)	(0.034)	(0.035)	(0.017)	(0.074)
$\widehat{\widehat{D}}$: Probability of ADHD								6.37^b
								(3.24)
$\widehat{\widehat{D}}\times$ AI								-1.08^b
								(0.49)
Age	0.015^a	0.015^a	0.015^a	0.015^a	0.057^a	0.015^c	-0.013^a	-0.11^a
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0099)	(0.011)	(0.0043)	(0.012)
Gender	0.52^a	0.52^a	0.52^a	0.52^a	0.52^a	0.526^a	0.47^a	-0.31
(1/0: 1 if Male)	(0.027)	(0.027)	(0.027)	(0.027)	(0.079)	(0.078)	(0.032)	(0.25)
Race	-0.30^a	-0.30^a	-0.29^a	-0.30^a	-0.053	-0.317^a	-0.35^a	-0.053
(1/0: 1 if African American)	(0.049)	(0.053)	(0.051)	(0.051)	(0.20)	(0.121)	(0.056)	(0.16)
Race	-0.17^a	-0.16^a	-0.17^a	-0.17^a	-0.24^b	-0.194	-0.18^a	0.017
(1/0: 1 if Other)	(0.053)	(0.053)	(0.053)	(0.053)	(0.10)	(0.168)	(0.066)	(0.14)
Ethnicity	-0.37^a	-0.37^a	-0.37^a	-0.37^a	-0.092	-0.388^b	-0.43^a	-0.027
(1/0: 1 if Hispanic)	(0.071)	(0.073)	(0.072)	(0.072)	(0.13)	(0.206)	(0.049)	(0.20)
Observations	49,527	49,527	49,527	49,527	6,714	6,714	49,513	4,701

Note 1: All specifications restrict the sample to children age 5-17 and excludes home-schooled and not in school children. Specifications (1) through (6) estimate Pr(ADHD=1). Specifications (1) through (4) include children in public schools (N= 49,527). Specification (5) is for children in private schools only (N=6,714). Specification (6) is the bootstrapped mean and sd over 900 replications for random samples of N=6,714 drawn from children in public schools. Specification (7) estimates Pr(Meds=1) for children in public schools (N=49,513) while specification (8) estimates Pr(Meds=1|ADHD=1) for children in public schools who are diagnosed with ADHD and for whom the medication status is known (N=4,701).
Note 2: Point estimates adjust for the weights provided in the data set. Standard errors are clustered by states and are in parentheses. Significance levels: (a,b,c) are 1,5 and 10% respectively.
Note 3: Column (6) shows the mean and standard deviation of the 1000 bootstraps (with replacement). The bootstraps adjust for the observation weights in the data set.

.011. Finally, when we use the sanctions law instead, the coefficient is .027 and is not statistically significant. The marginal effect for this third law is .0041 (at the sample mean while the mean of the marginals is .0039) with a p-value of .449. Thus, the first two laws appear to significantly increase the probability of diagnosis while the third does not have a significant impact on the probability of diagnosis. Two things are worth noting about these three results. First, these results are consistent with earlier results on aggregate consumption of psychostimulants where, for instance, assistance had the largest coefficient and was significant at $p < .01$ followed by the coefficients on the other two which were only significant at the 10% level (see Table 3 columns (3),(4) and (5)). Second, the signs of these coefficients are also consistent with the earlier descriptive statistics in Table 4. Even the lack of significance on the sanctions law is somewhat predictable, given the small difference in the conditional mean value of the sanctions law (.732 vs. .725) seen in Table 4.

Next, to access the joint impact of the three laws, we estimated a probit where we included a dummy variable for each of the three laws simultaneously (results not shown in the table but available from authors upon request). The coefficients on assistance and rewards were positive (.14 and .08 respectively) and significant (at p-values < .01 and .05 respectively) while the coefficient on sanctions was -.059 with a p-value < .1. Since the three laws are positively correlated with each other, this last result was unexpected and difficult to interpret. However, further inspection of the data revealed that the result was driven solely by one state, Alabama. In 2003, Alabama had the highest ADHD diagnosis rate in the nation, 12.67% among children in public schools (compared to the national average of 9.53%) and was also the *only* state where assistance and rewards laws were in effect but sanctions were not. Thus, in our sample, the percentage of children who are diagnosed with ADHD when all three laws are in effect (which is 13 states) is 10.84% while the percentage of children diagnosed with ADHD when assistance and rewards are in effect but not sanctions (which is just one state, i.e. Alabama) is 12.67%. To verify that the negative and significant coefficient on sanctions (conditional on assistance and rewards) is due to Alabama, we re-estimated the specification excluding observations from Alabama. The results for the dummy variable on rewards and assistance remained unchanged (both in magnitude and significance) while that for sanctions was no longer significant. In light of these results, we chose to construct an accountability index as the sum of the dummy variables (where the variable ranges from zero to three) and instead used that in the probit estimation. The results are shown in column (4). The coefficient on the index is .045 with a p-value < .01. The marginal effect at the mean is .0068 with a p-value equal to .002 (the mean of the marginals is .0066). Again this result mirrors that in column (8) in Table 3.

Finally, observe that in all four specifications, the coefficients on age and gender (male) are positive and significant while those on race (African Americans and Others) and Ethnicity (Hispanic) are negative and significant and do not change across the four specifications. These results are consistent with both the descriptive statistics as well as the (voluminous) literature on risk-factors associated with ADHD.

A Falsification Test. In order to check if these dummy variables are truly capturing the effect of accountability laws on the probability of being diagnosed, rather than some other unobserved factors at the state level correlated with ADHD diagnosis, we re-estimated the specification in column (4) on a sub-population where these laws should *not* have any effect: children enrolled in private schools, since the accountability laws only effect public schools. Results are given in column (5). Observe that the point estimate on the accountability index is much smaller and is not statistically significant. If in fact the accountability index was capturing the effect of other unobserved state level factors correlated with ADHD diagnosis, then we should expect to see the coefficient on the index to be similar to that in column (4), which it is not. Further, among the private school students, age and gender remain significant risk factors associated with diagnosis (and the coefficient on age increases) and the dummy variables on African-Americans and Hispanics are no longer significant. While these results suggest that the accountability index is really capturing the combined effect of the accountability laws and not of other unobserved factors (especially since the coefficients on age and gender remain significant – consistent with the literature on predictors of ADHD), the possibility remains that the lack of significance on the accountability index is simply a power issue as there are only 6,714 children in our sample for the private school population compared to 49,527 observations in the public school population. Thus, to further verify if this is indeed a power issue, we constructed 2000 random samples (with replacement) of size N=6,714 *from the public school population* and re-estimated the original probit on these sub-samples. The mean and standard deviation (i.e. the bootstrapped standard error) of the coefficients is reported in column (6). Observe that all the point estimates, including that on the accountability index, are now similar to those in column (4) and the coefficient on the accountability index is still significant at the 10% level. Results in column (5) and (6) together provide more confidence that the law index is in fact capturing the effects of accountability laws and not other unobserved factors correlated with the diagnosis.

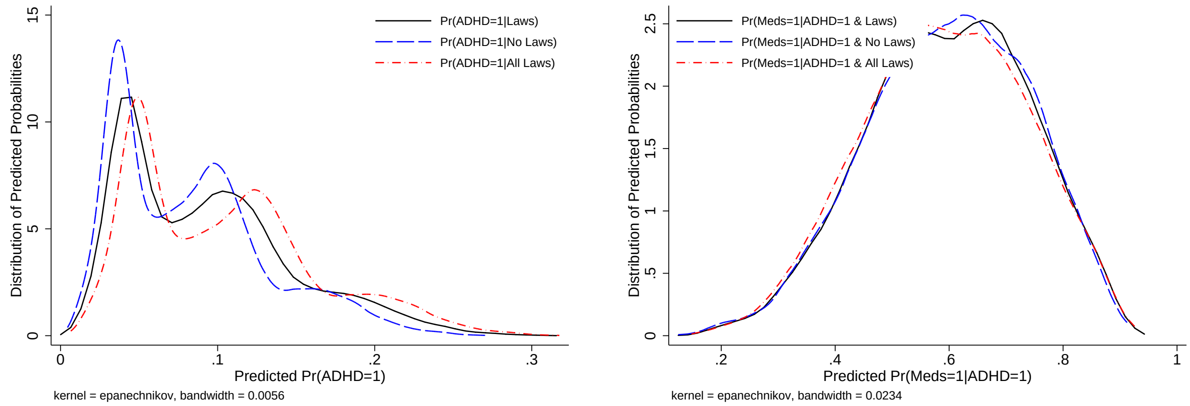
Probability of Medication. Next, to assess the impact of these laws on the probability of receiving medication therapy, we first estimated a simple probit on the full sample without regard to whether a child is ADHD or not (the sample reduces to 49,513 observations because we do not have medication information for 14 children). The results are shown in column (7). First, observe that the probability of medication, unlike the probability of diagnosis, *decreases* with age (as suggested by the descriptive statistics as well, see Table 4) and that females, non-white children and those of Hispanic origin are less likely to receive medication therapy. Next, the coefficient on the accountability index is positive and significant (.035, p-value = .037) and is consistent with the earlier aggregate analysis on total consumption. However, the marginal effect (for the probability of medication) with respect to the accountability index is much smaller than that computed earlier for probability of ADHD. The marginal effect for the probability of medication at the sample mean is .0035 (p-value = .036) while the mean marginal effect is .0039, indicating that every one point increase in the index (on a discrete scale from 0 to 3) on average increases the probability of medication by about .004. The marginal is understandably small in magnitude since we estimated this model on the full sample, i.e., children with and without ADHD diagnosis while the medication therapy can only be prescribed if a child is first diagnosed with ADHD.

Thus, we next estimated the probability of receiving medication therapy, conditional on having received an ADHD diagnosis via the specification given in Equation 2. Using probit coefficients from $Pr(D_i = 1)$, we computed $\widehat{\widehat{D}}_i = \Phi(X, L; \widehat{\beta})$ and used this value in the estimation of $Pr(M_i = 1|D_i = 1)$ on the sub-sample of children diagnosed with ADHD (N= 4,701). The variable $\widehat{\widehat{D}}_i$ can be interpreted as the estimated normalized value of the latent variable, i.e., the perceived severity of ADHD. Results are shown in column (8) in Table 5, but are not directly comparable to those in column (7) because the two probits are for different sub-populations (unconditional on ADHD versus those who are ADHD) and also because the specifications are different. The coefficient on the accountability index is not significant while that on $\widehat{\widehat{D}}_i$ is positive and significant and the coefficient for the interaction term is negative and significant. The mean marginal effect with respect to the accountability index is -.018 with a p-value of .22 while the marginal at the mean is -.021 (the computations of the marginals explicitly account for the presence of the interaction term).[8] Thus, conditional on the severity of ADHD (or the probability of being diagnosed with ADHD) the accountability laws do not effect the probability of medication therapy. In combination with the earlier results, total medication rate increases with the accountability laws because more children are diagnosed with ADHD, but once diagnosed, approximately 60% are prescribed medication therapy regardless of accountability laws.

Combined Effects. All three laws were in effect in 13 states while in another 12 none of the three laws were in effect. To assess the joint impact of these laws (or lack thereof) on the probability of diagnosis as well as on medication, we computed the model-predicted probabilities for specifications (3) and (8). The predicted probability of diagnosis ranged from .006 to .310 with a mean value of .093 (recall that in our sample 9.52% of the children are diagnosed with ADHD, see table 4). The distribution of predicted probabilities is right-skewed as shown on the panel on the left in Figure 1. The figure also shows the distribution of model-predicted probabilities of ADHD diagnosis for (a) if each child in the sample was in a state where there were no accountability laws, and (b) if each child in the sample was in a state where all three accountability laws were in effect. In the first case the mean probability is .083 while in the second case the mean probability is .104. Since nationwide

[8] Specifically, since the probability takes the form $Pr(M = 1|D = 1) = \Phi(\alpha_1 L_i + \alpha_2 \widehat{\widehat{D}}_i + \alpha_3 L_i \widehat{\widehat{D}}_i + \sum_{j=4} \alpha_j X_j +)$, then the marginal was computed as $\partial Pr(M = 1|D = 1)/\partial L_i = \phi(\cdot) \times (\alpha_1 + \alpha_3 \widehat{\widehat{D}}_i)$. This expression was evaluated for each observation in the sample to compute the mean marginal effect. Additionally, it was also evaluated at the sample mean (to compute the marginal at the mean) and the standard error was obtained via the delta method.

Figure 1. Distribution of (predicted) Probabilities



	$Pr(ADHD = 1)$				$Pr(Meds = 1 \mid ADHD = 1)$			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Laws as is	.093	.054	.006	.310	.599	.141	.148	.919
No Laws	.083	.049	.004	.271	.598	.141	.125	.917
All Laws	.104	.058	.007	.318	.593	.143	.148	.928

there are about 42,776,150 children in public schools, this difference in probabilities implies 936,600 additional children were diagnosed with ADHD due to these laws. Similarly, we also computed the model predicted probability of receiving medication therapy for each child with ADHD and conditional on their severity. The predicted probability ranged from .15 to .92 with the mean value of .599 (note that 58.76% of children with ADHD receive medication therapy). Figure 1 also shows the distribution of predicted probabilities along with the predicted distributions if all laws were in effect and when none were in effect. In these hypothetical cases, there is no significant shift in the distributions when there are no accountability laws versus when all three laws are present. Thus, of the 936,600 additional children diagnosed with ADHD (associated with the presence of these laws) approximately 59.8%, i.e., 560,882 are also prescribed medication therapy.

5. Summary and Conclusion

We used state level data on the consumption of psychostimulant drugs and relied on state and year variation in the provision of school accountability laws to identify the effect of these laws on consumption. Our results indicate that provisions of assistance to schools is associated with a 2.4% increase in consumption, and a one unit increase in the accountability index is associated with a 1.8% increase in consumption. While these results show that more stringent accountability laws have a significant impact on the aggregate consumption of psychostimulants, they do not reveal whether this increase is on the extensive or intensive margin, i.e., in association with the accountability laws, are more children being diagnosed with ADHD and hence the consumption rates increase, or is it that children already diagnosed with ADHD are more likely to be prescribed psychostimulant drugs. To this end, we used the NSCH data set and estimated a series of probability models. Our results indicate that these provisions increase the probability of being diagnosed with ADHD by .016 and .012 for assistance and rewards respectively and the marginal effect of the accountability index is .006. Further, conditional on ADHD diagnosis, the accountability laws do not change the probability of receiving medication therapy. Using the private school population, we also constructed a falsification test to check if other unobserved state level factors, which are correlated with accountability laws and effect the probability of ADHD diagnosis, are driving our results.

This study documents the unintended consequences of school accountability laws on medical diagnosis of children and their treatment options. While some schools may be inappropriately labeling marginal students as ADHD, it may also be that children who were previously undiagnosed and went undetected in over-crowded schools, are now detected and treated for their disorder. Nonetheless, it appears that at least some policy makers take the first view: Increasingly state and federal laws are being enacted that prevent teachers and other school personnel from requiring the use of a psychotropic drug for any student, especially as a precondition for attending classes. These laws are motivated in part by the concern that without such protections children are wrongly diagnosed and stigmatized as mentally disordered. However, some states have tightened such laws even further: Connecticut passed a law in 2001 (AB 5701) prohibiting school personnel from even *recommending* the use of psychotropic drugs to parents for any child, which was followed by similar laws in Illinois and Virginia in 2002 (SB 1719 and HB 90 respectively).

The intended and unintended consequences of school accountability have been actively studied in recent years, and a number of studies have demonstrated that school accountability laws are associated both with improved student outcomes as well as with a number of behavioral consequences. Among the more frequently studied accountability consequences is the effect of accountability on the classification of students with disabilities. Several studies have found that schools subject to more stringent accountability pressure tend to increase their rate of low-achieving students being served by special education services, leading observers to either argue that this is evidence of "gaming of the system" or alternatively of a role for accountability to help to identify students in need of services.

The present study expands upon this literature by investigating whether school accountability leads to medical diagnoses and medication therapy. This is important because these diagnoses require both school decision-making but also the professional judgment of physicians. While physician decisions on ADHD cases are certainly affected by input from school personnel, it provides an interesting opportunity for interpreting whether the behavioral consequences of accountability have been positive or negative, at least along this one dimension. Our first set of results on the probability of diagnosis show that in the presence of more stringent accountability laws, more children are likely to be diagnosed with ADHD. This result alone could be interpreted as a positive or negative effect of the laws since physicians' decisions are subject to input from school personnel. However, as previously noted (see page 4), drug therapy for ADHD children improves behavior as well as academic achievement and the academic achievement of their peers. Thus, there may be an incentive (among school personnel) to also influence the decision to initiate medication therapy among those who are diagnosed with ADHD but are not on medication therapy. Yet, conditional on diagnosis, our second set of results show that presence of more stringent accountability laws do not change the probability of receiving medication therapy. If physicians were simply reflecting the pressures felt by schools due to the accountability laws and not using independent judgment about diagnosis, we should have seen evidence of more ADHD children being prescribed medication therapy as well. These two results together *suggest* a positive, albeit unintended, consequence of the accountability laws, i.e., children who were previously undiagnosed and went undetected in over-crowded schools, are now detected and treated for their disorder.

Appendix A

Table 6. Regression of Log Quantity on State Accountability Laws

Dependent Var: Log Quantity (in gms) of all ADHD drugs w/ Amphetamine or Methylphenidate

(N = 240 All regressions)	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Report Cards Law	0.888 (0.317)	-0.0032 (0.013)							
Rates Law	0.638 (0.482)		0.013 (0.012)						
Assistance Law	0.567 (0.497)			0.034^a (0.0098)			0.032^a (0.010)	0.026^b (0.012)	
Rewards Law	0.350 (0.478)				0.020 (0.012)		0.013 (0.011)	0.013 (0.011)	
Sanctions Law	0.417 (0.494)					0.023^c (0.011)		0.012 (0.014)	
Accountability Index†	1.333 (1.134)								0.018^a (0.0052)
Year‡ 2000	0.200 (0.401)	0.18^a (0.037)	0.18^a (0.038)	0.18^a (0.037)	0.18^a (0.037)	0.18^a (0.036)	0.18^a (0.037)	0.18^a (0.037)	0.18^a (0.036)
Year‡ 2001	0.200 (0.401)	0.31^a (0.042)	0.31^a (0.044)	0.30^a (0.043)	0.31^a (0.043)	0.30^a (0.040)	0.30^a (0.044)	0.30^a (0.043)	0.30^a (0.041)
Year‡ 2002	0.200 (0.401)	0.47^a (0.051)	0.47^a (0.053)	0.47^a (0.053)	0.47^a (0.051)	0.46^a (0.049)	0.47^a (0.053)	0.46^a (0.052)	0.46^a (0.050)
Year‡ 2003	0.200 (0.401)	0.56^a (0.056)	0.55^a (0.060)	0.54^a (0.060)	0.56^a (0.057)	0.54^a (0.055)	0.55^a (0.060)	0.54^a (0.059)	0.54^a (0.057)
Ln Population	15.122 (0.992)	-0.56 (0.44)	-0.60 (0.45)	-0.55 (0.44)	-0.58 (0.47)	-0.62 (0.44)	-0.55 (0.46)	-0.58 (0.46)	-0.60 (0.46)
% Black Pop	10.518 (9.632)	0.030 (0.041)	0.028 (0.040)	0.031 (0.039)	0.021 (0.043)	0.032 (0.041)	0.025 (0.041)	0.026 (0.041)	0.024 (0.040)
% Other Pop	4.865 (3.192)	-0.037^c (0.020)	-0.035^c (0.021)	-0.035^c (0.021)	-0.037^c (0.020)	-0.034^c (0.019)	-0.036^c (0.021)	-0.035^c (0.020)	-0.035^c (0.019)
% Age 5-19	21.524 (1.293)	0.039^a (0.014)	0.041^a (0.014)	0.035^b (0.014)	0.037^a (0.014)	0.036^b (0.014)	0.034^b (0.014)	0.034^b (0.014)	0.033^b (0.014)
Ln Special Ed (Age 3-17)	11.316 (0.967)	0.20 (0.26)	0.18 (0.26)	0.16 (0.24)	0.18 (0.26)	0.16 (0.25)	0.15 (0.24)	0.14 (0.24)	0.14 (0.24)
Ln School Lunch Participation	12.804 (0.983)	-0.15 (0.24)	-0.14 (0.23)	-0.19 (0.22)	-0.12 (0.23)	-0.083 (0.24)	-0.16 (0.21)	-0.12 (0.21)	-0.087 (0.22)
Pupil Teacher Ratio	15.520 (2.286)	-0.0030 (0.0084)	-0.0041 (0.0081)	-0.0065 (0.0075)	-0.0029 (0.0085)	-0.0057 (0.0087)	-0.0061 (0.0076)	-0.0070 (0.0079)	-0.0068 (0.0084)

TABLE 6. Regression of Log Quantity on State Accountability Laws

Dependent Var: Log Quantity (in gms) of all ADHD drugs w/ Amphetamine or Methylphenidate

(N = 240 All regressions)	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	4.617	0.0046	0.0054	0.0051	0.0058	0.0060	0.0057	0.0063	0.0068
	(1.152)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Log Percapita Income	10.235	0.13	0.095	0.023	0.084	0.17	0.00072	0.038	0.066
	(0.145)	(0.34)	(0.34)	(0.32)	(0.35)	(0.34)	(0.32)	(0.33)	(0.33)
Percent Uninsured	13.740	0.0064	0.0062	0.0064^c	0.0067^c	0.0065	0.0066^c	0.0067^c	0.0068^c
	(3.872)	(0.0041)	(0.0040)	(0.0038)	(0.0039)	(0.0040)	(0.0037)	(0.0037)	(0.0037)
Ln Tot. Medicaid Compensation	21.703	0.017	0.022	0.019	0.0076	0.016	0.012	0.0098	0.0066
	(1.065)	(0.072)	(0.071)	(0.070)	(0.069)	(0.069)	(0.069)	(0.069)	(0.068)

Note 1: All regressions include state and year dummies. The sample consists of 48 States (Hawaii and Alaska excluded) and does not include D.C.
Note 2: a, b, c are significance levels at 1,5 and 10% respectively, and clustered (by state) standard errors are in parenthesis.
† Accountability index is the sum of dummy variables for Assistance, Sanctions and Rewards.

Table 7. Probability of ADHD Diagnosis and of Medication for ADHD

	Pr(ADHD=1)						Pr(Meds=1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assistance Law	0.11^a							
(1/0: 1 if State Law in effect)	(0.024)							
Rewards Law		0.077^b						
(1/0: 1 if State Law in effect)		(0.038)						
Sanctions Law			0.027					
(1/0: 1 if State Law in effect)			(0.036)					
AI: Accountability Index				0.045^a	-0.014	0.047^c	0.035^b	0.084
(Sum of the three laws)				(0.014)	(0.034)	(0.035)	(0.017)	(0.074)
$\widehat{D^*}$: Severity of ADHD								6.37^b
								(3.24)
$\widehat{D^*} \times$ AI								-1.08^b
								(0.49)
Age	0.015^a	0.015^a	0.015^a	0.015^a	0.057^a	0.015^c	-0.013^a	-0.11^a
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0099)	(0.011)	(0.0043)	(0.012)
Gender	0.52^a	0.52^a	0.52^a	0.52^a	0.52^a	0.526^a	0.47^a	-0.31
(1/0: 1 if Male)	(0.027)	(0.027)	(0.027)	(0.027)	(0.079)	(0.078)	(0.032)	(0.25)
Race	-0.30^a	-0.30^a	-0.29^a	-0.30^a	-0.053	-0.317^a	-0.35^a	-0.053
(1/0: 1 if African American)	(0.049)	(0.053)	(0.051)	(0.051)	(0.20)	(0.121)	(0.056)	(0.16)
Race	-0.17^a	-0.16^a	-0.17^a	-0.17^a	-0.24^b	-0.194	-0.18^a	0.017
(1/0: 1 if Other)	(0.053)	(0.053)	(0.053)	(0.053)	(0.10)	(0.168)	(0.066)	(0.14)
Ethnicity	-0.37^a	-0.37^a	-0.37^a	-0.37^a	-0.092	-0.388^b	-0.43^a	-0.027
(1/0: 1 if Hispanic)	(0.071)	(0.073)	(0.072)	(0.072)	(0.13)	(0.206)	(0.049)	(0.20)
Family Structure	0.33^a	0.33^a	0.33^a	0.33^a	0.46^a	0.327^a	0.23^a	-0.44^b
(1/0: 1 if Step Family, 2 Parents)	(0.041)	(0.041)	(0.041)	(0.041)	(0.11)	(0.107)	(0.045)	(0.22)
Family Structure	0.26^a	0.26^a	0.26^a	0.26^a	0.32^a	0.268^a	0.26^a	-0.15
(1/0: 1 if Single Mother, No Father)	(0.040)	(0.039)	(0.039)	(0.039)	(0.087)	(0.102)	(0.048)	(0.15)
Family Structure	0.17^a	0.17^a	0.17^a	0.17^a	0.12	0.163	0.068	-0.38^b
(1/0: 1 if Other)	(0.049)	(0.049)	(0.049)	(0.049)	(0.19)	(0.153)	(0.065)	(0.17)
Poverty Level	0.24^a	0.24^a	0.24^a	0.24^a	-0.011	0.235^c	0.072	-0.62^a
(1/0: 1 if < 100%)	(0.057)	(0.057)	(0.058)	(0.057)	(0.18)	(0.162)	(0.067)	(0.15)
Poverty Level	0.12^b	0.12^b	0.12^b	0.12^b	0.11	0.11	0.085	-0.22
(1/0: 1 if 100% to <133% P.L.)	(0.054)	(0.053)	(0.054)	(0.053)	(0.22)	(0.174)	(0.067)	(0.19)
Poverty Level	0.068	0.062	0.065	0.065	0.038	0.031	-0.075	-0.43^b
(1/0: 1 if 133% to <150% P.L.)	(0.077)	(0.077)	(0.078)	(0.077)	(0.37)	(0.235)	(0.085)	(0.21)
Poverty Level	0.049	0.049	0.049	0.049	0.14	0.048	0.072	-0.035
(1/0: 1 if 150% to <185% P.L.)	(0.039)	(0.039)	(0.039)	(0.039)	(0.14)	(0.166)	(0.058)	(0.22)

TABLE 7. Probability of ADHD Diagnosis and of Medication for ADHD

	Pr(ADHD=1)						Pr(Meds=1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poverty Level (1/0: 1 if 185% to <200% P.L.)	0.058 (0.055)	0.055 (0.055)	0.056 (0.055)	0.055 (0.055)	0.24 (0.23)	0.022 (0.215)	0.0074 (0.084)	-0.18 (0.19)
Poverty Level (1/0: 1 if 200% to <300% P.L.)	0.073^b (0.032)	0.072^b (0.032)	0.073^b (0.032)	0.073^b (0.032)	0.096 (0.26)	0.069 (0.113)	-0.014 (0.059)	-0.33^a (0.12)
Poverty Level (1/0: 1 if 300% to <400% P.L.)	-0.080^c (0.047)	-0.079 (0.048)	-0.079^c (0.047)	-0.079^c (0.048)	-0.084 (0.082)	-0.08 (0.112)	-0.078^b (0.039)	0.046 (0.076)
Highest Education in House Hold (1/0: 1 if Less than High SChool)	-0.023 (0.10)	-0.025 (0.10)	-0.022 (0.10)	-0.025 (0.10)	0.29 (0.25)	-0.055 (0.237)	0.048 (0.13)	0.16 (0.22)
Highest Education in House Hold (1/0: 1 if High School)	-0.011 (0.035)	-0.015 (0.036)	-0.011 (0.035)	-0.014 (0.035)	0.19^c (0.11)	-0.014 (0.101)	-0.0081 (0.033)	-0.031 (0.059)
% Age 5-19 (State-level Var)	-0.016 (0.016)	-0.0029 (0.015)	-0.017 (0.017)	-0.0076 (0.015)	0.040 (0.031)	-0.008 (0.039)	0.0020 (0.021)	0.015 (0.034)
Ln Special Ed (Age 3-17) (State-level Var)	-0.12^c (0.064)	-0.066 (0.076)	-0.14^b (0.065)	-0.078 (0.068)	0.12 (0.20)	-0.087 (0.189)	-0.19^b (0.094)	-0.32 (0.21)
Ln School Lunch Participation (State-level Var)	0.12^c (0.067)	0.088 (0.079)	0.16^b (0.070)	0.082 (0.073)	-0.052 (0.20)	0.086 (0.191)	0.20^c (0.10)	0.30 (0.22)
Pupil Teacher Ratio (State-level Var)	-0.0073 (0.0073)	-0.0094 (0.0059)	-0.0076 (0.0073)	-0.0097 (0.0065)	-0.0031 (0.015)	-0.011 (0.019)	-0.024^b (0.011)	-0.040^c (0.022)
Constant	-1.75^a (0.28)	-2.11^a (0.25)	-1.83^a (0.29)	-1.84^a (0.26)	-4.05^a (0.58)	-1.79^b (0.993)	-1.81^a (0.54)	1.56 (0.95)
Observations	49,527	49,527	49527	49,527	6,714	6,714	49,513	4,701

Note 1: All specifications restrict the sample to children age 5-17 and excludes home-schooled and not in school children. Specifications (1) through (6) estimate Pr(ADHD=1). Specifications (1) through (4) include children in public schools (N= 49,527). Specification (5) is for children in private schools only (N=6,714). Specification (6) is the bootstrapped mean and sd over 900 replications for random samples of N=6,714 drawn from children in public schools. Specification (7) estimates Pr(Meds=1) for children in public schools (N=49,513) while specification (8) estimates Pr(Meds=1|ADHD=1) for children in public schools who are diagnosed with ADHD and for whom the medication status is known (N=4,701).
Note 2: Point estimates adjust for the weights provided in the data set. Standard errors are clustered by states and are in parentheses. Significance levels: (a,b,c) are 1,5 and 10% respectively.
Note 3: Column (6) shows the mean and standard deviation of the 1000 bootstraps (with replacement). The bootstraps adjust for the observation weights in the data set.

References

Aizer, A. (2008, September). Peer effects and human capital accumulation: The externalities of ADD. NBER Working Paper 14354, National Bureau of Economic Research.

American Psychiatric Association (1994). *Diagnostic and Statistical Manual of Mental Disorders* (4 ed.). 4th. Edition.

Arcia, E., M. C. Fernandez, M. Jaquez, H. Castillo, and M. Ruiz (2004, November). Modes of entry into services for young children with disruptive behaviors. *Qualitative Health Research 14*(9), 1211–1226.

Barbaresi, W. J., S. K. Katusic, R. C. Colligan, A. L. Weaver, C. L. Leibson, and S. J. Jacobsen (2006, February). Long-term stimulant medication treatment of attention-deficit/hyperactivity disorder: Results from a population-based study. *Journal of Developmental & Behavioral Pediatrics 27*(1), 1–10.

Biederman, J. and S. V. Faraone (2006). The effects of attention-deficit/hyperactivity disorder on employment and household income. *Medscape General Medicine 8*(3), 12.

Brown, R., R. Amler, W. Freeman, J. Perrin, M. Stein, H. Feldman, K. Pierce, M. Wolraich, and American Academy of Pediatrics - Committee on Quality Improvement, Subcommittee on Attention-Deficit/Hyperactivity Disorder (2005, June). Treatment of Attention-Deficit/Hyperactivity Disorder: Overview of the evidence. *Pediatrics 115*(6), e749–e757.

Carlson, C. L., W. E. Pelham, R. Milich, and J. Dixon (1992, April). Single and combined effects of methylphenidate and behavior therapy on the classroom performance of children with attention-deficit hyperactivity disorder. *Journal of Abnormal Child Psychology 20*(2), 213–32.

Centers for Disease Control and Prevention (2005, September 2). Mental health in the United States: Prevalence of diagnosis and medication treatment for attention-deficit/hyperactivity disorder – United States, 2003. *Morbidity and Mortality Weekly Report 54*(34), 842–847.

Cullen, J. B. and R. Reback (2006, June). Tinkering toward accolades: School gaming under a performance accountability system. NBER Working Paper 12286, National Bureau of Economic Research.

Evans, S. W. and W. E. Pelham (1991, October). Psychostimulant effects on academic and behavioral measures for ADHD junior high school students in a lecture format classroom. *Journal of Abnormal Child Psychology 19*(5), 537–52.

Figlio, D. N. (2006). Testing, crime and punishment. *Journal of Public Economics 90*, 837–851.

Figlio, D. N. and L. S. Getzler (2006). Accountability, ability and disability: Gaming the system? In G. T. J. and D. W. Jansen (Eds.), *Improving School Accountability - Check-Ups or Choice*, Volume 14 of *Advances in Applied Microeconomics*, pp. 35–49. Elsevier.

Figlio, D. N. and J. Winicki (2005, February). Food for thought: the effects of school accountability plans on school nutrition. *Journal of Public Economics 89*(2-3), 381–394.

Greene, R. W., S. K. Beszterczey, T. Katzenstein, K. Park, and J. Goring (2002, Summer). Are students with ADHD more stressful to teach? patterns of teacher stress in an elementary school sample. *Journal of Emotional and Behavioral Disorders 10*(2), 79–89.

Jacob, B. A. (2005, June). Accountability, incentives and behavior: The impact of high-stakes testing in the Chicago public schools. *Journal of Public Economics 89*(5-6), 761–796.

Koretz, D. M. (1988). Arriving in Lake Wobegon: Are standardized tests exaggerating achievement and distorting instruction? *American Educator 12*(2), 8–15,46–52.

Koretz, D. M. (2002, Autumn). Limitations in the use of achievement tests as measures of educators' productivity. *Journal of Human Resources 37*(4), 752–777.

Koretz, D. M. and S. I. Barron (1998). The validity of gains in scores on the Kentucky instructional results information system (KIRIS). Rand Corp., Santa Monica, CA. Inst. for Education and Training.

Maddala, G. (1983). *Limited dependent and qualitative variables in econometrics*, Volume 3 of *Econometric Society Monographs.* New York: Cambridge University Press.

Mannuzza, S., R. Klein, A. Bessler, P. Malloy, and M. Hynes (1997, September). Educational and occupational outcome of hyperactive boys grown up. *Journal of the American Academy of Child and Adolescent Psychiatry 36*(9), 1222–1227.

MTA Cooperative Group, S. P. Hinshaw, G. R. Elliott, C. K. Conncers, K. C. Wells, J. March, J. Swanson, T. Wigal, D. P. Cantwell, H. Abikoff, L. Hecthman, L. Greenhill, and J. Newcorn (1999a, December). A 14-month randomized clinical trial of treatment strategies for ADHD. *Archives of General Psychiatry 56*, 1073–1086.

MTA Cooperative Group, S. P. Hinshaw, G. R. Elliott, C. K. Conncers, K. C. Wells, J. March, J. Swanson, T. Wigal, D. P. Cantwell, H. Abikoff, L. Hecthman, L. Greenhill, and J. Newcorn (1999b). Moderators and mediators of treatment response for children with ADHD: The MTA Study. *Archives of General Psychiatry 56*, 1088–1096.

Murphy, K. and R. A. Barkley (1996, November-December). Attention deficit hyperactivity disorder adults: comorbidities and adaptive impairments. *Comprehensive Psychiatry 37*(6), 393–401.

Neal, D. and D. W. Schanzenbach (2007, August). Left behind by design: Proficiency counts and test-based accountability. NBER Working Paper 13293, National Bureau of Economic Research.

Pelham, W. E., E. M. Gnagy, A. R. Greiner, B. Hoza, S. P. Hinshaw, J. M. Swanson, S. Simpson, C. Shapiro, O. Bukstein, C. Baron-Myak, and K. McBurnett (2000, December). Behavioral versus behavioral and pharmacological treatment in ADHD children attending a summer treatment program. *Journal of Abnormal Child Psychology 28*(6), 507–525.

Reback, R. (2008, June). Teaching to the rating: School accountability and the distribution of student achievement. *Journal of Public Economics 92*(5-6), 1394–1415.

Sax, L. and K. J. Kautz (2003, Sep-Oct). Who first suggests the diagnosis of attention-deficit/hyperactivity disorder. *Annales of Family Medicine 1*(3), 171–174.

Schneider, H. and D. Eisenberg (2006, April). Who receives a diagnosis of attention-deficit/ hyperactivity disorder in the United States elementary school population? *Pediatrics 117*(4), e601–e609.

Secnik, K., A. Swensen, and M. J. Lage (2005). Comorbidities and costs of adult patients diagnosed with attention-deficit hyperactivity disorder. *PharmacoEconomics 23*(1), 93–102.

U.S. Department of Education (2002). No child left behind: A desktop reference. Technical report, Office of Elementary and Secondary Education, Washington, D.C.