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The Effect of No Pass, No Drive Policies on High School Education

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Abstract

Since 1987, 27 states have introduced "No Pass, No Drive" laws tying a teenager's ability to receive and maintain a driver's license to various school-related outcomes – most commonly, enrollment and attendance. Using state-level data from the National Center for Education Statistics, this study examines how these policies affect dropout rates and four-year graduation rates. No Pass, No Drive policies targeting both enrollment and attendance have negligible effects on dropout rates, but decrease the Averaged Freshman Graduation Rate, one of the most commonly used four-year graduation rate estimates by researchers and policymakers over the past 10 years, by more than one percentage point. However, this lower graduation rate does not stem from a true reduction in the likelihood a student will graduate, but rather from students delaying their dropout decision by up to two years. In turn, these students are retained in the ninth and tenth grades, increasing ninth grade enrollment by 2.8 percent, relative to eighth grade enrollment the year prior, which lowers the graduation rate. Other No Pass, No Drive policies targeting only attendance increase dropout rates by more than one percentage point, as these policies revoke the driver's licenses of truants, but not dropouts.

1 Introduction

Over the past 30 years, attempting to lower dropout rates and raise graduation rates has been a central focal point of education policy on both the state and national level. At first glance, this increased attention has improved these two educational outcomes – The National Center for Education Statistics' (NCES) *Trends in High School Dropout and Completion Rates in the United States: 1972–2012* reports that the "status dropout rate," or the proportion of 16-24 year-olds who are not enrolled in high school and do not have a high school diploma or equivalency certificate, has fallen from 14.6 percent in 1972 to 6.6 percent in 2012. Likewise, the proportion of 18-24 year olds who have completed high school or an equivalent program has risen from 82.8 percent in 1972 to 91.3 percent in 2012. However, studies such as Cameron and Heckman (1993) and Heckman et al. (2011) show that simply completing high school or a GED is not enough to guarantee students' future success, but rather that *on-time* graduation with a regular high school diploma should be the goal of students aiming to increase their future earnings. In addition, Haney et al. (2004) show that the on-time graduation rate, which they estimate as the ratio of diploma recipients to "graduating" eighth graders four years prior, fell from 79% in the early 1980s to 74.4% in 2000-01. As a result, public policymakers have shifted their focus from ensuring teens complete high school to ensuring teens graduate from high school on time. This study focuses on No Pass, No Drive (NPND) laws – a widespread, low-cost incentive program tying teen drivers' licenses to their enrollment, attendance, behavior, and/or performance in school – and examines how NPND laws affect dropout rates, on-time graduation rates, and grade enrollment numbers across the country.

I show that No Pass, No Drive laws aimed at preventing dropouts have no significant effects on dropout rates. Instead, these policies cause a 1.3% *reduction* in the Averaged Freshman Graduation Rate (AFGR), an unintuitive result. I investigate two potential mechanisms for this graduation rate decrease. First, this could be caused by a reduction in the true four-year graduation rate; that is, the proportion of students that graduate from high school with a regular high school diploma within four years. Alternatively, the AFGR could fall as a result of students *delaying* their dropout decisions; a student who would drop out at the age of 16 in the absence of NPND laws may instead drop out at 18 in order to keep his or her drivers' license. If these delayed dropouts are retained in the 9th and/or 10th grades, then the dropout rate would be unaffected overall, but the denominator of the AFGR would be larger, causing a decline in the AFGR. I find that NPND policies cause a 2.8 percentage point increase in 9th grade enrollment, relative to 8th grade enrollment the year prior, suggesting that NPND policies delay student dropout decisions. I additionally test alternative graduation rate estimates that do not depend on 9th and 10th grade enrollment, and find no evidence to suggest that the true four-year graduation rate is affected by NPND policies. Given the importance of the AFGR in education reporting and policy-making decisions over the past 10 years, my results suggest that NPND policies artificially harm the public perception of education quality in these states, without significantly and directly affecting the true quality of education.

A second, smaller group of No Pass, No Drive laws is aimed at preventing truancy – a student who is enrolled in school and habitually absent will lose his or her driver's license. Importantly, however, these teens can drop out of school without penalty, and a teen who previously lost his or her license due to this law can even have their license reinstated (after a waiting period in some states). I show that this group of policies increases the event dropout rate, or the proportion of students who drop out of school in a single academic year, by 1.3 percentage points. These policies also cause a 2.65 percentage point decrease in 11th grade enrollment, relative to 10th grade enrollment the year prior, suggesting that the affected students are primarily dropping out of school in the 10th grade, the year when most students first obtain a driver's license and are first eligible to drop out of school.

In 1988, West Virginia enacted the first No Pass, No Drive law in response to growing problems with dropout rates and graduation rates, especially in rural areas. West Virginia, as do most states with NPND policies, mandates that teenagers must be enrolled in and attending school regularly in order to receive and maintain a driver's license. When students fall below a minimum attendance threshold, or withdraw from school entirely, the school contacts the state's licensing office and instructs them to suspend the teen's license. Early anecdotal evidence suggested that NPND policies were successful in their goal of keeping teens in school. In a 1989 New York Times article,[1] West Virginia school officials credited the enactment of the state's NPND law with a 1-2 percent reduction in the annual dropout rate (from approximately 5 percent to 3.4 percent). Following the early results in West Virginia, 26 more states enacted their own versions of NPND policies in an effort to recreate the early success of West Virginia's policy. I look at the enactment of these 27 policies, exploiting variation in the timing of their enactment between states, to identify the causal effects of these policies on various educational outcomes.

Krimmel (2000) was the first to perform an empirical study of the effects of No Pass, No Drive policies on educational outcomes. His time-series analysis of a quasi-natural experiment in Ken-

[1] "West Virginia Reduces Dropouts by Denying them Driver's License." *The New York Times,* May 21, 1989.

tucky showed that counties that enacted NPND laws saw an 11 percent reduction in the dropout rate, while the comparison group of counties that did not enact NPND laws only saw an 8 percent reduction in the dropout rate. My analysis differs from Krimmel's in a few key dimensions. First, my analysis is on a national level, exploiting timing differences in the enactment of NPND policies to identify their effects, while Krimmel's only identifies the effect of Kentucky's NPND laws. Thus, my results should provide greater external validity in informing policy decisions. Second, Krimmel only investigates the effects of NPND laws on dropout rates, while I am able to identify the effects of NPND laws on four-year graduation rates, individual grade enrollments, and dropout rates. Finally, and most importantly, Krimmel's policy analysis is conflated with the simultaneous enactment of dropout prevention counseling programs in the treatment counties, meaning that Krimmel's results should be interpreted as the effect of NPND laws in conjunction with dropout prevention counseling, while my analysis, by examining these policies nationwide and exploiting heterogeneous timing of NPND enactment, is able to identify the impact of NPND policies separately and more accurately.

The only other paper, to my knowledge, to empirically study No Pass, No Drive policies is the work of Barua and Vidal-Fernandez (2014). They study NPND policies on a national level, primarily focusing on the effects of NPND policies on student time use, as well as examining educational attainment. They show that NPND policies increase the proportion of 18-24 year-olds who have a high school diploma by approximately 1 percentage point, and demonstrate stronger effects on males (1.5%), blacks (3-4%), and particularly black males (4-7%). They also demonstrate that educational attainment increases by 0.02 to 0.05 years on average, and that students spend approximately 0.2 more hours per week on schoolwork as a result of NPND laws. My results do not necessarily contradict those of Barua and Vidal-Fernandez, as we consider different outcome variables in our analyses. However, while Barua and Vidal-Fernandez show a number of unambiguous positive effects of NPND policies, with no costs to the government other than monitoring costs, I demonstrate that the largest group of laws cause a sharp increase in grade retention in 9th and 10th grades, without causing a similarly large increase in the number of graduates. Additionally, even though NPND laws seem to be successful in increasing educational attainment and diploma recipiency, as demonstrated by Barua and Vidal-Fernandez, I show that, since a nationwide study of NPND policies would primarily capture the enrollment-based policies, these increases come primarily from delayed dropout decisions, not from an increase in on-time graduation.

My analysis of No Pass, No Drive policies consists of three main contributions to the literature on NPND laws, and, more generally, incentive programs and their effects on teen behavior. First, I examine the effects of NPND policies on dropout rates and the Averaged Freshman Graduation Rate, a widely-used estimate of the on-time graduation rate. Second, I demonstrate an issue with using the AFGR as a measure of policy outcomes – that the AFGR can be significantly biased in the presence of policies and programs that affect enrollment in the 9th and 10th grades. Specifically, I show that rather than reducing the number or true rate of graduates, which would contradict the findings of Barua and Vidal-Fernandez, these NPND policies increase enrollment in 9th and 10th grades relative to their initial cohort size in 8th grade. This provides an interesting scenario – enrollment-based NPND policies do not appear to lower the *true* four-year graduation rate, but significantly lower four-year graduation rate *estimates*. This reduction in the on-time graduation rate estimate is also not unique to the AFGR; any estimate that includes 9th or 10th grade enrollment in the denominator will be negatively affected by enrollment-based NPND policies.

I conclude my analysis by discussing two of the effects that enrollment-based NPND policies have on education, given that they increase grade enrollment and lower the AFGR. First, and perhaps most importantly, the AFGR was the benchmark graduation rate statistic used by the U.S. Department of Education from 2004-2012 under the No Child Left Behind Act (NCLB) to determine Adequate Yearly Progress (AYP). NPND policies, by lowering the AFGR, decreased the likelihood of schools, districts, and states of meeting their respective AYP standards, and likely resulted in a number of schools being designated for "improvement" that, in the absence of NPND policies, would have otherwise met their graduation rate goals. Second, by increasing enrollment in the 9th and 10th grade, NPND policies likely increased negative externalities on those students whose behavior was not changed by these laws. Students who, in the absence of NPND policies, would have dropped out of school at the age of 16 are instead retained in the 9th and 10th grades, and may have behavioral and learning problems that would negatively affect their peers.

The remainder of this paper is organized as follows: Section 2 explains the details of No Pass, No Drive Policies, including lists of each policy across the country, as well as their attributes. Section 3 describes the data sources and estimation strategy employed. Section 4 presents the primary results, explains the forces driving my results, and presents a set of robustness checks to demonstrate validity of my models, as well as show a lack of alternative explanations for my results. Section 5 discusses the impacts No Pass, No Drive policies have on schools and their students under No Child Left Behind, and Section 6 provides concluding remarks.

2 The No Pass, No Drive Policy

Starting with West Virginia in 1988, 27 states have passed laws linking student behavior, attendance, and performance to their ability to receive and maintain a drivers' license. Differing from the previous work on these policies, I categorize these policies into groups to more closely examine the effectiveness of the various incentives. For example, the first of these policies, in West Virginia, only allows a license to be held by a student who *"maintains current school enrollment and is making satisfactory academic progress"*.[2] The policy in Kansas, however, states that *"Whenever a pupil who has attained the age of 13 years has been found in possession of a weapon or illegal drug at school, . . . the division of vehicles immediately shall suspend the pupil's driver's license or privilege to operate a motor vehicle."*[3] A third type of policy in California states that *"Any minor under the age of 18 years, but 13 years of age or older, who is an habitual truant . . . may have his or her driving privilege suspended for one year by the court."*[4] Clearly, these are three different policies, attempting to curb different problems, and so examining them as if they were a single policy aimed at reducing dropout rates and raising graduation rates would inaccurately identify

[2]West Virginia Annotated Code, §17B-2-3a(2)(E)
[3]Kansas Statute Annotated, §72-89c02(a)-(c)
[4]California Vehicle Code, §13202.7

the full effect of those policies that do target these rates. To solve this, I classify the policies into three groups – *Enrollment-Based* policies, as in West Virginia, which directly target high school dropouts, *Truancy-Based* policies, as in California, which target truants and not dropouts, and *Behavior-Based* policies, as in Kansas, which target school discipline. These groupings, as well as some unique features of these policies, are shown in Table 1.

Except for the case of Kentucky (see footnote 6), no NPND policy has ever been repealed; all 27 of these policies are currently ongoing. Implementing many of these policies requires coordinated efforts between local education agencies and the drivers' license issuing offices. For example, some states, such as Kentucky, have an electronic communication system in place between schools and the Kentucky Division of Motor Vehicle Licensing, so that a student failing to meet the requirements to keep his or her license at school will be automatically "flagged" in the system. Then the Kentucky DMV will examine the student's record and determine whether there is justification to suspend his or her license. In contrast, states like Texas have no such electronic communication system in place. Instead, students in Texas must take a form confirming their enrollment and attendance for past 180 days in to the Texas Department of Public Safety in order to receive a learner's permit at age 15, to receive a graduated drivers' license at age 16, and to renew the license at age 17. Thus, heterogeneity across states in reporting student activity is present. However, due to the subjectiveness of attempting to categorize these systems, as well as uncertainty on how such electronic systems have been implemented over time, I am unable to examine the effects of differing reporting systems on student outcomes.

3 Data and Methods

3.1 Data

I collected information on the details of these policies from each state's code of laws and legislative histories. I then merged this policy information with data on student outcomes and school spending taken from the National Center for Education Statistics. The NCES's Common Core of

Table 1: No Pass, No Drive Policies in the United States

State Name	Policy Start Year	Hardship/Working Exemption?	GED Exemption?	Other
Enrollment-Based				
Alabama	1993	Yes	No	Teen parents exempt
Arkansas	1989	Yes	No	
Florida	1997	Yes	Yes	
Georgia	1998	No	No	
Idaho	1996	No	No	
Illinois	2007	No	No	
Indiana	1991	Yes	No	
Iowa	1994	No[5]	No	
Kentucky	1990, 2007[6]	Yes	No	
Louisiana	2009	No	No	
Mississippi	1994	No	No	
North Carolina	1998	Yes	No	
Ohio	2004	No	Yes	
Oklahoma	1996	Yes	No	
Oregon	2000	No	Yes	
South Carolina	1998	No	No	
Tennessee	1990	No	No	
Texas	1995	No	No	
West Virginia	1988	No	No	
Wisconsin	1988	No	No	Only some counties enacted policy
State Name	**Policy Start Year**	**Truants Only?**	**Discipline Only?**	**Other**
Truancy-Based				
California	1992	Yes	No	
Delaware	2000	Yes	No	
Nevada	2003	Yes	No	
New Mexico	2005	Yes	No	
Behavior-Based				
Kansas	1999	No	Yes	
Louisiana	2004[7]	No	Yes	
Oregon	1995[7]	No	Yes	
Rhode Island	2005	No	Yes	
Virginia	1996	No	No	Exempt with parental permission

Data (CCD) has public-use state-level data on dropout rates, graduation rates, diploma counts,

[5]In the original version of this policy, Iowa had an exemption for working students. This exemption was removed in 2005.

[6]Kentucky instituted this policy in 1990 in some counties; however, the law was struck down by the Kentucky Supreme Court in 2003 (*D.F. v Codell*). A new law, identical to the original for the purposes of this research, was

and enrollments. Data on grade enrollments from grade 8 to grade 12, as well as total diploma recipients, were taken from the State Nonfiscal Public Elementary/Secondary Education Survey datasets available on the NCES website. I merged the individual data files from 1986-87 to 2012-13, assembling a panel dataset. The data are missing the number of diplomas in 1986-87, as well as from 2010-11 to 2012-13. For school years from 2005-06 to 2009-10, data on the number of diploma recipients in each state were taken from the CCD's State Dropout and Completion Data Files.

Graduation rates are unavailable in a consistent and accurate form across all years of my dataset. With the passage of the No Child Left Behind Act (NCLB) in 2001, the US Department of Education (DoE) mandated that states begin implementing more accurate measures of four-year graduation rates. As a result, attempting to link the NCES's graduation rates, which are self-reported by each state, and do not follow a consistent formula, before and after 2001 would create severe inconsistencies in my analysis. To circumvent this issue, I use the Averaged Freshman Graduation Rate (AFGR), proposed by Greene and Winters (2002), which is an easily calculable graduation rate statistic that only requires state-level grade enrollment data. The AFGR was the standard graduation rate used by the US DoE from 2005-2012 in determining school- and district-level adequate yearly progress under NCLB, and is generally considered to be a good estimate of on-time graduation rates, given limited available data.[8] The AFGR is calculated for each state (s), in every year (t) using the formula below:

$$AFGR_{s,t} = \frac{Diplomas_{s,t} * 3}{Grade\ 8_{s,t-4} + Grade\ 9_{s,t-3} + Grade\ 10_{s,t-2}} * 100\%$$

Simply put, the AFGR uses the average enrollment for a single cohort from 8th to 10th grade as the "enrollment base" from which the four-year graduation rate is calculated. I use the AFGR, as opposed to educational attainment in the full population as in Barua and Vidal-Fernandez, to provide a policy analysis more aligned with the interests of policy makers and educational agencies.

implemented in 2007.

[7]Louisiana and Oregon initially had Behavior-Based policies focusing on discipline, but then changed to Enrollment-Based policies focusing on dropouts at a later date.

[8]See Heckman and LaFontaine (2012) for an overview of various graduation rate statistics used in the United States, and a comparison of the AFGR to graduation rate estimates from other sources.

The US DoE's Race to the Top program, implemented in 2011, challenges states to achieve four-year graduation rates of 90% by the year 2020, so a four-year graduation rate is a more appropriate statistic to study than overall educational attainment in a state-level policy analysis such as this.

Dropout rates were taken from the NCES's annual *Dropout Rates in the United States* reports. The NCES uses an *event dropout rate* definition, which is calculated as the total number of students that drop out of school in a given year, divided by total enrollment in that year. This is in contrast to other agencies that report *status dropout rates*, which are the fraction of people of schooling age (typically ages 15-21) that are not currently enrolled in school and have not completed school. Since these No Pass, No Drive policies typically have grandfathering clauses, where students that have already dropped out of school before the policy takes effect do not lose their licenses, the event dropout rate is a more appropriate statistic for examining the early years of the policy. Additionally, status dropout rates typically consider individuals up to age 21, while NPND policies only affect those under the age of 18. I also took data on total expenditures on public schooling per pupil from the NCES's Elementary/Secondary Information System (ELSi), and state unemployment rates were taken from the Bureau of Labor Statistics.

3.2 Model Specification

I aim to identify the impact of No Pass, No Drive laws on state average dropout rates and graduation rates. This is done by exploiting variation in the time of passage of these laws among the twenty states with Enrollment-Based policies, the four states with Truancy-Based policies, and the three states with Behavior-Based policies. The primary regression model of interest is below:

$$Y_{st} = \beta_0 + \beta_1 EnrollBased_{st} + \beta_2 TruancyBased_{st} + \beta_3 BehaviorBased_{st} + \varepsilon_{st}$$

Above, the variables Enroll-Based, Truancy-Based, and Behavior-Based are binary – $EnrollBased_{st}$ is set equal to 1 if state s has an Enrollment-Based policy in place at time t and equal to 0 otherwise, and likewise for Truancy- and Behavior-Based. The outcome variable, Y_{st}, is either the dropout rate or AFGR, depending on the regression.

In order to account for differences in educational quality and economic climate between the states with and without these policies, I include a pair of control variables mentioned previously – per-student public schooling expenditures and state unemployment rates. I also include state and year fixed effects to control for baseline differences between states and the overall downward trends observed in both dropout rates and graduation rates over the past 25 years. Finally, I include state-specific linear time trends to correct for additional state-level trends in dropout rates and graduation rates differing from the overall trend. A cursory glance at the data suggests that states that initially have low dropout rates and/or graduation rates saw those numbers fall to a lesser extent than states with high rates. The primary regression model used for analysis is below:

$$\begin{aligned} Y_{st} =& \beta_0 + \beta_1 EnrollBased_{st} + \beta_2 TruancyBased_{st} + \beta_3 BehaviorBased_{st} \\ &+ \beta_4 log(Spending)_{st} + \beta_5 Unemp_{st} + \delta_t + \gamma_s + \gamma_s * t + \varepsilon_{st} \end{aligned}$$

The coefficients β_1, β_2, and β_3 are the parameters of interest in this regression, and should be interpreted as the causal effect of these No Pass, No Drive policies on dropout rates and graduation rates.

4 Results

Table 2 shows the primary regression results, using the model specification described in Section 3.2 and the dropout rate as the dependent variable. Column (1) shows the naïve regression results on dropout rates, demonstrating that the states with the No Pass, No Drive policies have below-average dropout rates. Columns (3) and (4) include the full set of controls, and are the main results of this regression. It is important to note here that, based on the event dropout rate definition, the coefficient on any policy would not be influenced by students *delaying* their dropout decision. So, for example, if a student subject to one of these policies at age 16 decides to drop out of school

Table 2: Effects of No Pass, No Drive Policies on Dropouts

	Dropout Rate			
	(1)	(2)	(3)	(4)
Enrollment-Based	-0.929**	0.125	0.272	0.174
	(0.351)	(0.346)	(0.375)	(0.364)
Other Policies	-0.250	1.018***	1.050**	
	(0.513)	(0.295)	(0.276)	
Truancy-Based				1.229**
				(0.263)
Behavior-Based				0.393
				(0.648)
Fixed Effects and Trends?		Yes	Yes	Yes
School and Macro Controls?			Yes	Yes
N	869	869	818	818

Standard errors in parentheses, clustered by state.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Truancy-based p-values are bootstrapped as in Cameron et al. (2008)

at age 18, when they no longer are affected by the policy, the policy coefficient would remain unchanged. Looking at columns (3) and (4), Enrollment-Based policies have no significant effect on dropout rates, indicating that any students who do change their behavior based on this policy are delaying their dropout decision. Truancy-Based policies, alternatively, cause increase the dropout rate by 1.229 percentage points per year – the mean dropout rate is 4.23%, so approximately 29% more students drop out of school each year than would have otherwise. Recall the incentives at work in these policies – a habitual truant will lose his or her driving privileges, but a dropout will not in these states.

Section A in the appendix describes a threat to my identification, and my solution to the problem. In Table A in the appendix, placebo testing shows that analysis on the truancy-based policies suffers from severe type I error; to correct for this, I use the wild restricted cluster bootstrap-t as in Cameron et al. (2008). This method corrects for type I error in difference-in-differences estimation, and allows for proper statistical inference. In Table 2 and the remainder of the paper, all reported standard errors are the typical cluster-robust standard errors. However, the Enrollment-based policies use the typical t-distribution in hypothesis testing, while the Truancy- and Behavior-based policies use a t-distribution generated from the bootstrap procedure. The cluster-robust standard error estimates are presented, as opposed to a bootstrapped standard error estimate, because the cluster-robust estimate is used to calculate the Wald statistic used for inference. The bootstrap procedure in Cameron et al. tests the Wald statistic generated from my estimation against a bootstrap t-distribution of Wald statistics, so the appropriate standard error to report is the typical cluster-robust standard error estimate. Based on this procedure, the coefficients and standard error estimates presented in all tables are unaffected by the bootstrap procedure, and only the p-values and significance indicators are affected for the Truancy- and Behavior-Based policy coefficients. Table 3 shows the primary regression results on Averaged Freshman Graduation Rates.

Table 3: Effects of No Pass, No Drive Policies on AFGR

	Averaged Freshman Graduation Rate			
	(1)	(2)	(3)	(4)
Enrollment-Based	-3.667*	-1.133	-1.330*	-1.139
	(1.932)	(0.816)	(0.763)	(0.764)
Other Policies	-4.949**	-2.628*	-2.732**	
	(2.244)	(1.461)	(1.448)	
Truancy-Based				-4.999*
				(2.365)
Behavior-Based				0.597
				(1.103)
Fixed Effects and Trends?		Yes	Yes	Yes
School and Macro Controls?			Yes	Yes
N	1018	1018	1018	1018

Standard errors in parentheses, clustered by state.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Truancy-based p-values are bootstrapped as in Cameron et al. (2008)

Again, column (1) shows the naïve regression results, demonstrating that the states with No Pass, No Drive policies have below average AFGRs. Interestingly, however, after including the full set of controls, column (3) shows the treatment effect of the policy is still negative, implying that these policies are reducing graduation rates in some meaningful way. Additionally, adding the spending and unemployment controls in moving from column (2) to column (3) increased the magnitude of the coefficient estimate and decreased the standard error, suggesting that omitted variable bias is unlikely to be the force driving this surprising result. For Truancy-Based policies, this could potentially be explained by the increase in dropout rates observed in the previous set of regressions. Column (4) shows that the states that target truants have a negative effect on AFGR, while the other Behavior-Based states have a positive, but insignificant effect. However, this does not explain the negative coefficient on the Enrollment-Based policy. The following section investigates the potential causes of this AFGR reduction.

4.1 No Pass, No Drive Laws and the AFGR

Based on the way in which AFGR is calculated, there are two mechanisms by which these No Pass, No Drive policies could be reducing the AFGR in Table 3. The policy could be decreasing the numerator – that is, reducing the number of diplomas handed out each year. This is likely the cause of the large, negative Truancy-Based coefficient, but is unlikely for Enrollment-Based policies; the incentives created by these Enrollment-Based NPND policies would in no way lead me to expect students to respond by failing to graduate. Alternatively, this policy could be increasing the denominator – that is, increasing enrollment in 8th, 9th, and/or 10th grades. In addressing these two possibilities, an important feature of the US education system needs to be mentioned – the so-called "ninth grade bottleneck".

A number of papers have noted that ninth grade retention rates are extremely high in the United States, and have grown drastically over the past 50-60 years. McCallumore and Sparapani (2010) estimate that approximately 22% of students repeat at least some 9th grade classes. This has increased 9th grade enrollment to the point where it is an entirely inaccurate measure of a single grade cohort's size. The AFGR was created, in part, to correct for this very issue; it reduces the impact of 9th grade enrollment on graduation rates by factoring in estimated cohort size, using 8th and 10th grade enrollments to smooth the estimated enrollment base. To identify the effect the No Pass, No Drive policies have on the AFGR, I first consider how these policies affect year-to-year enrollment changes for a particular cohort. Using the CCD enrollment data I construct a number of dependent variables showing year-to-year enrollment changes for a single cohort. For example, the 8th to 9th grade enrollment change is calculated as:

$$\%\ Change\ 8th - 9th_{s,t} = \frac{9th\ Grade\ Enrollment_{s,t} - 8th\ Grade\ Enrollment_{s,t-1}}{8th\ Grade\ Enrollment_{s,t-1}} * 100\%$$

Alternatively, I could use log(Enrollment) as the dependent variable in these regressions. I use the percentage changes in grade enrollment to better account for between-cohort variation in size, and also to more clearly show the lack of promotion out of the 9th grade. Table 4 shows summary statistics for year-to-year enrollment changes by grade for a single cohort.

Table 4: Year-to-Year Enrollment Changes by Cohort

	Overall Average 1987-2012	Average in 1990	Average in 2010
8th to 9th change	+11.286%	+11.271%	+9.952%
9th to 10th change	-7.932%	-7.524%	-6.686%
10th to 11th change	-8.364%	-8.802%	-6.913%
11th to 12th change	-6.389%	-9.084%	-1.778%
12 Grade Graduation Rate	90.261%	97.449%	91.151%[9]

Source: Common Core of Data

Table 4 demonstrates the overall pooling effect of 9th grade – a great number of students repeat the 9th grade at least once. In addition, many students will repeat the 9th grade until they drop out of school. 9th grade retention rates have fallen since 1990, likely due to improvements in school quality and the introduction of policies directed at reducing this effect. However, it still

[9] Diploma counts for 2010 were unavailable at the time of writing; this number is the 2009 12th Grade Graduation Rate.

remains true that 9th grade enrollments are much larger than would be expected given 8th grade enrollments – indicating that 9th grade retention is still a problem. Raw dropout counts show that 9th grade dropouts and 11th grade dropouts are roughly equal in number; however, due to compulsory schooling until the age of 16, 9th graders should be unable to drop out of school unless they have repeated a grade.[10] The table above shows that, on average, total 9th grade enrollment is approximately 11 percent greater than total 8th grade enrollment for a single cohort. After 9th grade, enrollment numbers fall every year as one would expect. Although the AFGR was created to reduce the bias caused by this effect, if these policies are causing a disparate impact in any one grade then the AFGR would be still be influenced, even if the "true" four-year graduation rate is unaffected. I begin by directly examining the effect of NPND policies on the 9th grade bottleneck, and then show that a reduction in graduates is not the cause of the AFGR decline. Table 5 looks at the 9th grade bottleneck, showing results from a regression specified identically to the previous regressions examining dropout and graduation rates, including the same set of controls, but using percentage enrollment changes as the dependent variable.

Table 5 shows important effects of the Enrollment-Based policies. First, note in column (1) that the coefficient on per-student spending is large, negative, and significant. This indicates that the 9th grade pooling effect is alleviated by improving funding and school quality. Compare this to the Enrollment-Based policy effect; the policy increases the gap between 8th and 9th grade enrollment, and it may make the 9th to 10th grade attrition rate larger as well, although this coefficient is not significant. Clearly, this is evidence that the Enrollment-Based policy increases the rate of pooling in 9th grade, constricting the 9th grade bottleneck to an even greater degree than before the policy was implemented. To understand why this occurs, consider the type of student affected by this policy – before the policy, many students were dropping out of school at the age of 16, but with the policy, they wait until they turn 18. The results in Table 2 indicated that dropout rates were not significantly affected by this policy, so it must be that the policy is simply causing students to delay their dropout decision. Without the policy, many of these "marginal" students – those that

[10] *Numbers and Rates of Public High School Dropouts: School Year 2004-05* shows 125,115 9th graders and 125,882 11th graders dropped out of school in 2004-05.

Table 5: Effects of No Pass, No Drive Policies on Grade Enrollments

	Percentage Change in Enrollment			
	8th-9th (1)	9th-10th (2)	10th-11th (3)	11th-12th (4)
Enrollment-Based	2.792**	-1.651	-0.653	0.333
	(1.281)	(1.040)	(0.710)	(0.539)
Truancy-Based	-0.0158	-0.169	-2.769*	0.859
	(2.021)	(1.927)	(1.677)	(1.434)
Behavior-Based	-0.260	1.673	-1.444	0.955
	(0.748)	(0.671)	(1.119)	(0.565)
log(Spending)	-14.43**	3.864	-1.659	-5.341*
	(6.241)	(6.248)	(5.989)	(3.041)
Unemp. Rate	-0.575	-0.177	-0.166	-0.0017
	(0.352)	(0.244)	(0.305)	(0.196)
All specifications include two-way fixed effects, school and macro controls, and state-specific time trends.				
N	1071	1071	1071	1071

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Truancy- and Behavior-based p-values are bootstrapped as in Cameron et al. (2008)

would have changed their behavior under these No Pass, No Drive policies – are retained in 9th grade until they drop out at age 16. With the policy, the primary difference is that these marginal students are retained in 9th grade until they drop out at age 18.

Additionally, Table 5 verifies the results from Table 2 regarding the effects of Truancy-based policies on dropout rates. The majority of states in the time period examined had compulsory schooling until the age of 16, and also allowed students to receive their driver's license at the age of 16. Since students who are progressing through school normally will be 16 years old in the 10th grade, the result in column (3) is entirely expected – truant teens drop out of school at the first available opportunity, making the gap between 10th and 11th grade enrollment larger.

The alternative explanation for the AFGR falling due to the Enrollment-based policies, as in the summary statistics previously, is a decrease in the numerator of the AFGR statistic – that these policies reduce the number of diplomas given out in some meaningful way. I test for this in two ways; first, by using the 12th grade graduation rate, calculated as before as the ratio of diplomas to 12th grade enrollment in a given academic year. I also consider a simple five-year graduation rate – calculated as the ratio of diplomas to 8th grade enrollment five years prior. The five-year graduation rate should not be affected by 9th grade pooling, and so it should be a less noisy measure of on-time high school graduation, especially given the pooling caused by NPND policies. If these policies are actually making students graduate at a lower rate, instead of artificially lowering the AFGR statistic via increasing 9th grade enrollments, the coefficient estimates for these two specifications, especially the five-year graduation rate, should be negative and significant. Table 6 shows the effects of NPND policies on these two graduation rate estimates.

Column (1) shows the effect on the percentage of 12th graders that graduate in a given year. No policy has a significant effect, but both groups are negative and around 1. However, this is a far less accurate measure of a possible effect of these policies on graduation than the five-year graduation rate. If some of the "marginal" students under Enrollment-based policies – those who would drop out at age 16 without the policy but instead wait until they turn 18 – move through school on-track, meaning they are in 12th grade when they turn 18, then it is reasonable to assume that not only might these students drop out of the 12th grade, but also the average ability of 12th graders would decrease as a result of the policy. Likewise, some truants in Truancy-based states may drop out at age 17 in order to retain their license, biasing the estimate in column (2) downward. A more accurate measure of how these policies affect on-time graduation rates is the five-year graduation rate. Column (3) shows that the Enrollment-Based policy effect is negative, relatively small, and insignificant. Truancy-based policies appear to cause extremely large, but insignificant decreases in the five-year graduation rate, but the other policies do not have an effect. All of this evidence suggests that, while the Truancy-Based policies reduce *actual* graduation rates and increase dropout rates, the Enrollment-Based policies only *artificially* reduce the AFGR by

Table 6: Effects of No Pass, No Drive Policies on Alternative Graduation Rates

	12th Grade Grad. Rate		5-Year Grad. Rate	
	(1)	(2)	(3)	(4)
Enrollment-Based	-0.928	-0.847	-0.738	-0.479
	(1.122)	(1.115)	(0.729)	(0.724)
Other Policies	-1.218		-3.657	
	(0.716)		(1.827)	
Truancy-Based		-2.490		-6.422
		(1.077)		(2.981)
Behavior-Based		0.113		0.0187
		(1.095)		(0.862)
log(Spending)	11.43*	11.22*	2.352	1.718
	(5.822)	(5.835)	(6.109)	(6.177)
Unemp. Rate	0.571	0.555	0.263	0.219
	(0.356)	(0.362)	(0.279)	(0.284)
All specifications include two-way fixed effects and state-specific time trends.				
N	1018	1018	1018	1018

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Truancy-based p-values are bootstrapped as in Cameron et al. (2008)

increasing 9th grade enrollment. To demonstrate the effects Enrollment-Based NPND policies have on overall enrollment more clearly, Figure 1 shows, for every 1,000 8th graders, how many students are expected to be enrolled at each grade level.

In Figure 1, the “Without NPND” bars show the average year-to-year enrollment changes among all 23 states that never begin a NPND policy. The “With NPND” bars add the Enrollment-based regression results from Table 5 to the “Without NPND” averages, meaning that the “With NPND” effects show the expected results of a state enacting NPND laws among the states that do not currently have NPND laws. The number atop each bar shows the estimated size of the gap between

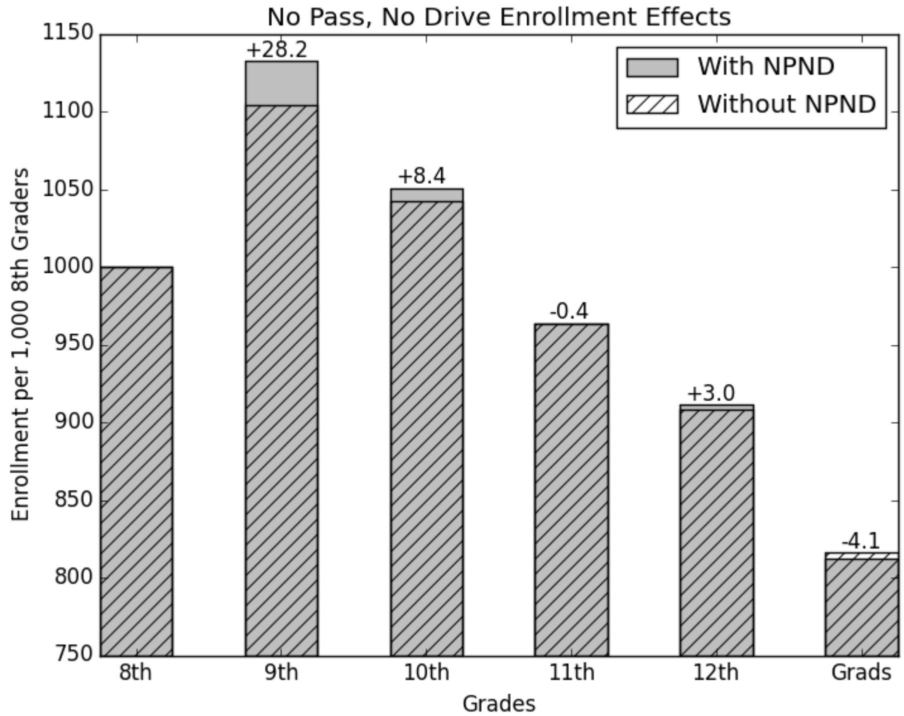


Figure 1: Effects of No Pass, No Drive Policies on Enrollment

the states with and without NPND policies. There are a few key effects of the NPND policies that clearly reveal themselves in this graph. First, NPND laws have the largest effect in 9th grade. For every 1000 8th graders, 9th grade enrollment increases by more than 28 students as a result of these policies. Second, the negative coefficient on the 9th to 10th grade enrollment change does not cancel out the large, positive coefficient on the 8th to 9th grade enrollment change – 10th grade enrollment is also larger than expected, given 8th grade enrollment. Finally, the remaining coefficients essentially cancel out the remaining effect. That is, 11th and 12th grade enrollments and diploma counts are essentially identical, comparing NPND states to their counterparts without NPND laws. Additionally, recall that none of the coefficients after the 8th to 9th grade change were significantly different from zero. As a result, Figure 1 may be underestimating the size of 10th, 11th, and 12th grades, as well as the number of diplomas. Overall, the massive increase in

9th grade enrollment and the smaller increase in 10th grade enrollment are much more likely to be the causes of the AFGR reduction than a decline in high school graduates.

4.2 Additional Robustness Checks

A potential concern with these results is the classic "Ashenfelter's Dip" problem – the enactment of these policies may have been preceded by, and possibly even caused by, a short-term shock to state educational outcomes. If this is true, then my regression results could be caused by simple mean reversion instead of any true causal effect of the policy. To consider this, I test the three years before the policy begins for deviations from the state-specific trends. Table 7 shows the results of these regressions.

Table 7: Pre-Policy Variation in AFGR, Dropout Rates, and Enrollment Changes

	Dropout Rate			AFGR			% Change 8th-9th		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Years Before Policy									
Enrollment-Based: 1	0.00738			-0.0492			0.331		
	(0.0829)			(0.172)			(0.327)		
Enrollment-Based: 2		-0.0385			-0.368**			0.671**	
		(0.0773)			(0.148)			(0.251)	
Enrollment-Based: 3			0.0353			-0.113			0.384
			(0.0843)			(0.173)			(0.321)
Behavior-Based: 1	0.270*			-0.393			-0.256		
	(0.137)			(0.302)			(0.698)		
Behavior-Based: 2		0.0375			0.0894			-0.563	
		(0.107)			(0.292)			(0.612)	
Behavior-Based: 3			-0.0671			0.308			-0.340
			(0.189)			(0.465)			(1.557)
N	818	818	818	1018	1018	1018	1071	1071	1071

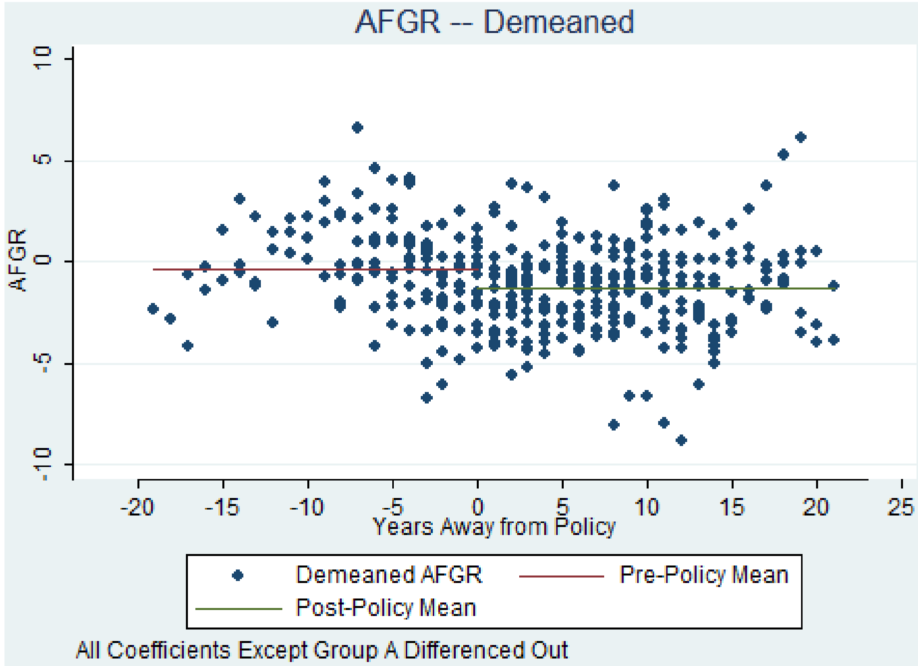
Standard errors in parentheses, clustered by state
Spending and unemployment controls, two-way fixed effects, and state-specific time trends included in all models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Columns (5) and (8) of Table 7 are the only ones that show any significance for Enrollment-

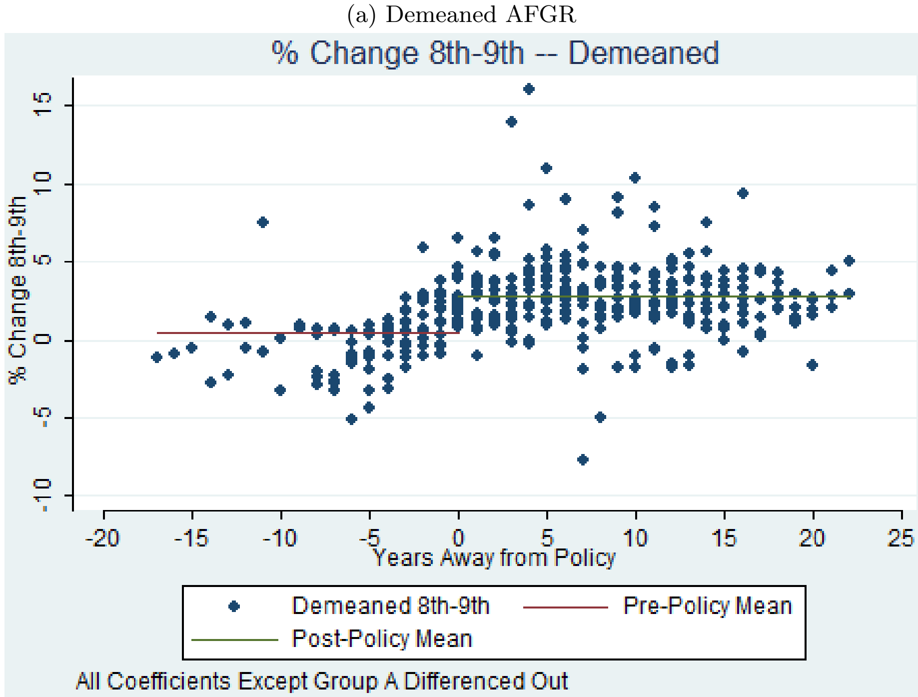
Based policies. However, instead of being a mean reversion concern, these coefficient estimates are in the same direction as the main results in Tables 3 and 5. This could mean that the coefficient estimates in Tables 3 and 5 are caused by some omitted variable bias, but these pre-policy coefficient estimates are much smaller in magnitude than the main result, implying that the start of these NPND policies is the major driving force behind the main set of results. To further demonstrate this, in Figure 2 I also graph the AFGR and 8th-9th grade percentage change data for the states that enacted Enrollment-based policies, removing the effects of all other covariates, to demonstrate the lack of evidence for an Ashenfelter's dip situation.

In Figure 2, Graphs (a) and (b) show the trend of the AFGR and 8th-9th grade percentage change, relative to the enactment of the NPND policy in Enrollment-Based states. Note that in both of these figures, Oregon and Louisiana were excluded. Both of these states enacted Behavior-Based policies five years before enacting Enrollment-Based policies, and so including these states in the plots would conflate any pre-policy effects of the Enrollment-Based policies with post-policy effects of Behavior-Based policies.[11] Graph (a) shows a small decline in the AFGR after the policy is enacted, but this does not have any noticeable timing effects. There is a possible small pre-policy dip in the AFGR, especially in the lowest-performing states, but the post-policy effect is an overall lower AFGR than in the pre-policy years. In Graph (b), the effect of the policy is much more noticeable. The 8th-9th grade enrollment change was relatively constant before the policy was enacted, and rose to a new, higher, but still relatively flat level after the policy was enacted. Both of these results suggest that NPND policies are truly lowering the AFGR by increasing 9th grade retention.

[11] I have also run the AFGR and 8th-9th grade enrollment change regressions excluding all observations from Louisiana and Oregon. The results are qualitatively identical (although the AFGR result is no longer significant), and are included in Table C in the appendix.



(a) Demeaned AFGR



(b) Demeaned % Change 8th-9th

Figure 2: Trends in AFGR and the 8th-9th Grade Enrollment Gap

5 Discussion

5.1 No Child Left Behind and the AFGR

Upon passage of the No Child Left Behind Act in 2001, states were pushed to improve test scores, attendance rates, and graduation rates nationwide. Each state was given the option to design its own standards for educational accountability, subject to a few guidelines. Each school district was required to report to the state educational agency various annual measures of Adequate Yearly Progress (AYP), that would determine the district's and schools' levels and status of federal education funding. The National High School Center reported that, for all schools, AYP was required to be measured along five dimensions – reading and mathematics proficiency, testing participation rates in reading and mathematics, and "at least one other academic indicator". High schools were given the additional requirement that the other academic indicator must be a measure of on-time graduation, while middle and elementary schools typically would use daily attendance rates. Schools failing to meet the AYP standards created by their state's educational agency for two consecutive years were designated as needing improvement. The school would then be required to allow all its students the option to transfer to another school satisfying AYP, likely losing some funding as a result. Each subsequent year of failing to meet the AYP standards would result in more harsh penalties, until, after five consecutive years of failing to meet AYP, the school would be required to undergo "restructuring". Restructuring often would take the form of either reorganizing a public school into a charter or specialized school, or a massive replacement of the faculty and administration at the school.

Given the effects of NPND policies on enrollments and graduation rates that I have demonstrated, it is straightforward to understand the impact these policies had on Adequate Yearly Progress. Since these policies cause a strengthening of the ninth-grade bottleneck, causing a reduction in the AFGR, high schools in states with NPND laws will have a more difficult time reaching the required graduation rate under AYP. As I mentioned previously, from 2005 to 2012 the US DoE used the AFGR as its standard graduation rate statistic[12], meaning that states with these NPND policies were inadvertently harming their Adequate Yearly Progress.

These negative AFGR effects will likely have differential effects on states' AYP, depending on the actions of each state's educational agencies. One potential outcome of this is that states with NPND laws would have high rates of failure to meet AYP, resulting in high rates of "designation for improvement" and high restructuring rates. This is the most expected outcome, as NPND laws would make it more difficult for schools to reach the AYP levels. However, there are a few other possibilities – for example, instead of causing a large percentage of schools to fail to meet AYP, states could instead simply create lower standards for AYP in response to declining graduation rates. By doing this, schools would not be at lower risk of failing to meet the AYP standards, causing fewer schools to undergo restructuring, but the stated goals of No Child Left Behind – improving academic achievement and educational attainment among US youth – would essentially be ignored. Additionally, as reported by a number of news agencies, various cheating and data falsification scandals have occurred in order to keep schools and districts above the minimum AYP standards.[13] No Pass, No Drive policies, and the lower AFGR that accompanies them, would create greater incentives to falsify and misreport graduation rate data.

5.2 No Pass, No Drive and the Ninth Grade Bottleneck

Over the past 30-40 years, high school enrollment trends have changed drastically. As I mentioned previously, enrollment numbers in ninth grade now exceed both eighth and tenth grade, and there is some evidence that ninth grade enrollment is the highest of *all* grades. Haney et al. (2004) show that in academic year 1999-2000, ninth grade enrollment was the highest of all grades, K-12, nationwide, while in academic year 1968-69, ninth grade enrollment was only the highest out of

[12]From 2005 to 2012, the US DoE funded improved data collection and student tracking measures, resulting in the current standard graduation rate, implemented nationwide in 2013 – the Adjusted Cohort Graduation Rate (ACGR). The ACGR tracks all students individually through high school, so it would not be negatively impacted by NPND policies.

[13]See "ON EDUCATION; The 'Zero Dropout' Miracle: Alas! Alack! A Texas Tall Tale." *The New York Times*, August 13, 2003 for an example of dropout and graduation rate falsification in Houston, TX.

grades 8-12. Many researchers in education have written on the causes of this ninth grade bottleneck – Haney and Madaus (1978) were the first to notice this growing issue, and suggested that the introduction of minimum competency testing in the early 1970s may be the cause. Regardless of the cause, however, my results show that No Pass, No Drive policies exacerbate the situation – ninth grade enrollment increases relative to both eighth and tenth grade enrollments as a result of this policy.

Given the impact of NPND policies on grade retention, then, it is important to consider how grade retention affects long-term outcomes both for students being retained and for students not being retained, but possibly experiencing externalities resulting from their retained peers. Jacob and Lefgren (2009) study a test score-based grade promotion method in Chicago using a regression discontinuity framework, and find that eighth graders retained due to insufficient test scores face an increased likelihood of dropping out of 8-15 percent, relative to their peers that met the minimum test score requirement for promotion. In addition, retained eighth graders were approximately 22 percent less likely to graduate from high school than their promoted peers. For eighth graders, and conceivably for ninth graders, grade retention does not appear to improve educational outcomes for the retained students. The NPND policies would conceivably have slightly different effects than high-stakes testing – students repeating the ninth grade multiple times under NPND are likely those that would have dropped out had the policy not been in place – but any positive effects of the NPND on those retained students would be minute at best.

The externalities created by higher ninth grade enrollment, however, may be more noticeable. No Pass, No Drive policies will have a definite impact on school quality through the No Child Left Behind mechanisms mentioned in the previous section, but the direction and magnitude of this impact is uncertain. Schools that are designated as "needing improvement" receive additional attention and funding, but are subject to a more rigorous set of educational standards, the impact of which is not readily identifiable. Schools could receive this additional funding and improve the quality of their schools, or they could panic after receiving this additional scrutiny, discouraging students from achieving higher academic standards. A stark example of this occurred in Birmingham, AL in 2000, when 522 students were dismissed from Birmingham Public Schools due to fears that those students would lower their schools scores on state standardized testing (Orel 2003). Additionally, negative externalities related to both increased class sizes and the type of student being retained in ninth grade could impact student achievement. Angrist and Lavy (1999) show that Israeli fourth and fifth graders have significantly higher test scores in smaller classes. Since NPND laws would likely increase average class sizes in the ninth grade, this may negatively affect student test scores. Carrell and Hoekstra (2010) consider the externalities created by children exposed to domestic violence. They show that children exposed to domestic violence significantly lower the math and reading test scores of their peers. NPND policies are likely keeping troubled teens in the classroom, where they distract their peers and disrupt the learning environment, causing negative impacts on the achievement of their peers. Consequently, these negative externalities may even be amplifying the effects of NPND policies; not only are some "marginal" dropouts being retained in the ninth grade for up to two more years, they also may be causing some of their peers, who in the absence of NPND policies would have been promoted to tenth grade, to be retained alongside them.

6 Conclusion

Overall, No Pass, No Drive policies do not appear to be as unambiguously beneficial to educational outcomes as previous studies have found. While my analysis supports previous results that educational attainment increases due to the enactment of Enrollment-based NPND policies, this increase seems to, at most, marginally improve the number of high school graduates in the population, and does not improve the number of *on-time* high school graduates. This slight increase in educational attainment also carries with it some significant, but previously unnoticed, costs. Enrollment in 9th grade, relative to 8th grade, increases by nearly 3 percent, and enrollment in 10th grade increases by approximately 1 percent. This puts pressure on state and local education budgets, as higher student enrollment numbers would require the hiring of additional teachers and staff, as well as increased overall spending on student services and needs ranging from cafeteria lunches to textbook purchases. Additionally, as discussed previously, the students being retained in school as a result of these NPND policies are the "marginal dropouts" who are nearly indifferent between dropping out of school and remaining in school in the absence of the NPND policies. These students likely have an increased prevalence of behavioral and learning issues, which may be imposing negative externalities on their peers, raising the cost of NPND policies by reducing educational quality for the non-dropout students in these states. Add to this the fact that, for nearly a decade, NPND policies increased the likelihood for schools to fail to meet their Adequate Yearly Progress standards under the No Child Left Behind Act, and it is clear that Enrollment-based NPND policies have a number of substantial, but previously unnoticed, problems.

Perhaps of greater immediate concern to policymakers are the effects of Truancy-based No Pass, No Drive policies on teen decision-making. As opposed to Enrollment-based policies, which delay the dropout decision of some teens in a way that does not affect the dropout rate or true four-year graduation rate, Truancy-based policies cause a large and unambiguous increase in the dropout rate and an associated decrease in the four-year graduation rate. By creating new punishments for truancy, without an associated penalty for dropping out, these policies have distorted the incentives of teen students in a way that, for many students, makes dropping out of school a more appealing option than either remaining in school as a truant or increasing their school attendance to comply with the NPND policy. I calculate that Truancy-based policies increase the number of dropouts in the United States by over 27,000 teens *per year*,[14] showing that, despite the relative rarity of these policies, the overall effect is quite large.

Moving forward, policy makers need to reevaluate the goals of No Pass, No Drive policies and examine how the results of these policies align with their goals. If the goal is simply to keep teenagers in school, potentially causing reductions in outcomes such as juvenile crime and teen pregnancy, then Enrollment-based NPND laws appear to successfully achieve this goal – my

[14]High school enrollment for California, Delaware, Nevada, and New Mexico in 2012-13 was about 2.2 million, multiplied by the Truancy-based coefficient from Table 2.

results show that 9th and 10th grade enrollment increases, without bringing associated decreases in 11th or 12th grade enrollments. However, if the goal of NPND policies is to improve students' educational outcomes, then a major revision of these policies is needed. Enrollment-based NPND policies increase educational attainment for marginal dropouts, but impose substantial costs on their schools and the overall student population; Truancy-based NPND policies increase the dropout rate, but potentially reduce costs on schools and the overall student population. While the AFGR was replaced in 2012 by the ACGR in calculations of Adequate Yearly Progress, it is still one of the most widely cited graduation rate statistics by both news reporting agencies and lawmakers; thus, the fact that Enrollment-based NPND laws lower the AFGR should in itself be of great concern to policy makers. Add to this that the increased 9th and 10th grade enrollments create negative externalities on the students whose decisions were not directly influenced by this group of NPND laws, and it appears that all NPND laws likely have a negative overall effect on both the true quality of education (through negative externalities and shifts in resource allocation by educational agencies for Enrollment-based policies and through an increase in the dropout rate for Truancy-based policies) and the perceived quality of education, as measured by the AFGR and dropout rate.

References

Angrist, Joshua D. and Victor Lavy. "Using Maimonides' Rule to Estimate the Effect of Class Size on Scholastic Achievement." *The Quarterly Journal of Economics.* 114: 2 (1999), 533-75.

Ashenfelter, Orley. "Estimating the Effect of Training Programs on Earnings." *The Review of Economics and Statistics* 60: 1 (1978), 45-57.

Ayres, B. Drummond Jr."West Virginia Reduces Dropouts by Denying them Driver's License." *The New York Times* (1989, May 21.) Retrieved from http://www.nytimes.com

Barua, Rashmi and Marian Vidal-Fernandez. "No Pass No Drive: Education and Allocation of Time." *Journal of Human Capital* 8: 4 (2014), 399-431.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics* 119: 1 (2004), 249-75.

Cameron, Stephen V. and James J. Heckman. "The Nonequivalence of High School Equivalents." *Journal of Labor Economics* 11: 1 (1993), 1-47.

Carrell, Scott E. and Mark L. Hoekstra. "Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids." *American Economic Journal: Applied Economics.* 2: 1 (2010), 211-28.

D.F. v. Codell, 127 S.W.3d 571 (Ky. 2003).

Greene, Jay P. and Marcus A. Winters. "Public School Graduation Rates in the United States." Center for Civic Innovation at the Manhattan Institute, No. 31, 2002.

Haney, Walt and George Madaus. "Making Sense of the Competency Testing Movement." *Harvard Educational Review* 48: 4 (1978), 462-84.

Haney, Walt, George Madaus, Lisa Abrams, Anne Wheelock, Jing Miao, and Ileana Gruia. *The Education Pipeline in the United States 1970-2000.* The National Board on Educational Testing and Public Policy: Lynch School of Education, Boston College (2004).

Heckman, James J., John Eric Humphries, and Nicholas S. Mader. "The GED." In Eric A. Hanushek, Stephen J. Machin, and Ludger Woessmann (Eds.), *Handbook of the Economics of Education, Vol. 3.* San Diego, CA: Elsevier.

Jacob, Brian A. and Lars Lefgren. "The Effect of Grade Retention on High School Completion." *American Economic Journal: Applied Economics* 1: 3 (2009), 33-58.

Kansas Statute Annotated, §72-89c02(a)-(c).

Krimmel, John T. "An Examination of Kentucky's 'No Pass–No Drive Bill'." *Education Research Quarterly* 23: 4 (2000), 27.

McCallumore, Kyle M. and Ervin F. Sparapani. "The Importance of the Ninth Grade on High School Graduation Rates and Student Success in High School." *Education* 130: 3 (2010), 447-56.

National Center for Education Statistics, *Common Core of Data: State Nonfiscal Public Elementary/Secondary Education Survey 1986-2012.* (Washington, DC: National Center for Education Statistics, Institute of Education Sciences).

_________________ *Common Core of Data: Dropouts, Completers, and Graduation Rate Reports 2005-2009.* (Washington, DC: National Center for Education Statistics, Institute of Education Sciences). *Common Core of Data: State Nonfiscal Public Elementary/Secondary Education Survey 1986-2012.* (Washington, DC: National Center for Education Statistics, Institute of Education Sciences).

_________________ *Common Core of Data: National Public Education Financial Survey Data 1986-2012.* (Washington, DC: National Center for Education Statistics, Institute of Education Sciences).

_________________ *Common Core of Data: Number and Rates of Public High School Dropouts: School Year 2004-05.* (Washington, DC: National Center for Education Statistics, Institute of Education Sciences).

National High School Center, *At a Glance: NCLB and High Schools.* (Washington, DC: The National High School Center at the American Institutes for Research in collaboration with Learning Point Associates, MDRC, the National Center for Educational Accountability, the National Dropout Prevention Center/Network, the National Dropout Prevention Center for Students with Disabilities, and WestEd).

Orel, Steve. "Left Behind in Birmingham: 522 Pushed Out Students." in Lent, ReLeah C. and Gloria Pipkin. *Silent No More: Voices of Courage in American Schools.* Portsmouth, NH: Heinemann, 1-14.

U.S. Bureau of Labor Statistics, *Local Area Unemployment Statistics: 1986-2013.* (Washington, DC: Bureau of Labor Statistics, Local Area Unemployment Statistics Information and Analysis).

U.S. Census Bureau, *Population Estimates: Intercensal Estimates 1990-2000, 2000-2010.* (Washington, DC: U.S. Census Bureau, Population Estimates Project).

U.S. Congress, No Child Left Behind Act of 2001, 20 USC 6301, Public Law 107–110 (2002).

West Virginia Annotated Code, §17B-2-3a(2)(E).

Winerip, Michael. "ON EDUCATION; The 'Zero Dropout' Miracle: Alas! Alack! A Texas Tall Tale." *The New York Times* (2003, August 13). Retrieved from http://www.nytimes.com

Appendix: Placebo Testing and Bootstrapping

A possible concern with my results is that the data may be structured in a way that causes a high rate of type I error. For example, data with an extremely high level of variation in the dependent variables could cause overrejection of the null hypothesis, and thus any regression results would be largely uninterpretable. Bertrand et al. (2004) demonstrate that difference-in-difference estimation often suffers from overrejection of the null hypothesis, caused by serial correlation in the dependent variable. Since my dependent variable certainly has serial correlation, this could be causing my standard errors to be too small, creating type I error. To examine this problem, I mimic the methodology of Bertrand et al., by creating a group of "placebo policies", where the policies are randomly assigned to various states, but in a similar way to how they are actually distributed across the United States. For Enrollment-Based policies, each state is given a 40% chance to begin the placebo policy so that in expectation, the number of states with the policy will be 20, the same as the number of Enrollment-Based states. In testing Truancy-Based policies, states are given an 8% chance to begin the placebo policy. After these states are selected, a "policy enactment year" is randomly selected from the discrete uniform distribution, with the earliest possible start year being 1987. Then, regression models identical to my main specifications are run and the placebo policy treatment coefficient is tested at the same significance level of my actual result to see if my results are at risk of type 1 error. In addition, I test for symmetry by performing both 1- and 2-tailed significance tests. If the data is structured in a way that causes overrejection of the null hypothesis in only one direction, this could also be cause for concern. For regression models where I did not find significance, I test for type II error by running these models and testing the placebo policy treatment coefficient at the $p<0.1$ level. I simulate these placebo policy assignments for 10,000 replications, and calculate the simulated rejection rate I observe. The results of these placebo tests are summarized in Table 8.

The Enrollment-Based placebo testing yielded no unexpected results – in all regression models, the rejection probability was extremely close to its expected level. However, the Truancy-Based placebo testing demonstrated severe type I error – testing dropout rates at the 1% significance level,

Table A: Placebo Policy Testing Results

	Significance Level (Tails)	Rejection Percentage
Enrollment-Based – 40% Chance to Begin Placebo Policy		
Dropout Rate	0.1 (2)	11.19%
AFGR	0.05 (1)	5.68%
AFGR	0.1 (2)	11.27%
12th Grade Grad. Rate	0.1 (2)	10.90%
5-Year Grad. Rate	0.1 (2)	10.85%
Percentage Changes		
8th-9th	0.025 (1)	2.63%
8th-9th	0.05 (2)	4.94%
9th-10th	0.1 (2)	10.35%
10th-11th	0.1 (2)	10.38%
11th-12th	0.1 (2)	10.78%
Truancy-Based – 8% Chance to Begin Placebo Policy		
Dropout Rate	0.005 (1)	8.93%
Dropout Rate	0.01 (2)	21.05%
AFGR	0.05 (2)	26.21%
AFGR	0.025 (1)	12.05%
12th Grade Grad. Rate	0.05 (2)	24.18%
12th Grade Grad. Rate	0.025 (1)	11.47%
5-Year Grad. Rate	0.1 (2)	25.44%
5-Year Grad. Rate	0.05 (1)	11.61%
Percentage Changes		
8th-9th	0.1 (2)	30.13%
9th-10th	0.1 (2)	31.90%
10th-11th	0.1 (2)	25.45%
11th-12th	0.1 (2)	30.39%

the null hypothesis was rejected over 20% of the time. All other measures also showed high rates of rejection for Truancy-Based policies. This indicates that using OLS standard errors is inappropriate for this analysis. The Enrollment-Based policy results, however, do not seem to face this problem, and are therefore unlikely to be driven by pure chance.

To correct for the type I error demonstrated by my Placebo testing, I follow the methodology of Cameron et al. (2008) and use the wild restricted cluster bootstrap-t statistic for statistical inference on Truancy-based policies. In their analysis, Cameron et al. test the setup of Bertrand et al. (2004), and show that by using the wild cluster bootstrap-t, they can achieve rejection rates with little to no Type I error. In performing this test, the standard cluster-robust variance estimate is use to calculate the standard errors, but the Wald statistic generated from this estimate is tested against the bootstrap distribution of Wald statistics. Table B shows the Wald statistic for each regression, and the p-value from testing this against the bootstrap Wald distribution (B=10,000).

Table B: Bootstrapping Results

Dependent Variable	t-statistic	p-value
Dropout Rate	5.90	0.011
AFGR	-2.36	0.071
% Change 9th-10th	0.60	0.603
% Change 10th-11th	-1.90	0.074
% Change 11th-12th	-0.56	0.627
5-Year Grad. Rate	-2.15	0.307
12th Grade Grad. Rate	2.43	0.522

All specifications test Truancy-Based policies.

All Truancy-based policies denoted with statistical significance in the main body of the paper reflect these bootstrapped p-values. From these results, three of the seven main regressions in my analysis show statistical significance for at least $p < 0.1$.

Appendix: Additional Tables and Figures

Table C: Effects on AFGR and Enrollment,
Excluding Louisiana and Oregon

	(1)	(2)
	AFGR	8th-9th Enrollment Change
Enrollment-Based	-1.125	2.449*
	(0.802)	(1.246)
Behavior-Based	-2.207	-1.257
	(2.107)	(0.888)
log(Spending)	5.249	-15.63**
	(5.950)	(6.437)
Unemp. Rate	0.304	-0.513
	(0.311)	(0.359)
N	978	1029

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