EVALUATING THE IMPACT OF PERMANENT SCHOOL CLOSURE

by

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DEDICATION

To Chief: the pug who inspires me.

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ABSTRACT

In any given school year, about seven percent of all U.S. public school districts will close one of its schools. In the years directly following the Great Recession, school closure increased by up to 5 percentage points. School closures can be devastating events that disrupt student and teacher routines, separate peer groups, and potentially overextend the resources of receiving schools. As a result, they are usually the last result of a school district to decrease funding. Closing a school allows districts to reduce spending by decreasing expenditures on building maintenance and operation. School closure was a tool used by districts to alleviate the financial distress following the extreme negative effects on public education caused by the Great Recession. During the recent Covid-19 pandemic, state funds began to follow similar trajectories to the 2008 recession. Thus, we ask ourselves "what could we have done differently in response to the Great Recession?" This question is worth examining as it allows us to develop better policy in the wake of budget shocks that U.S. districts almost faced.

While a closure is hard on a district, it can also provide a unique opportunity to re-allocate resources within the district to be more efficiently allocated. In normal years, tenure makes teacher re-allocation difficult, but the significant change in the educational environment brought about by closure can provide an opportunity to re-orient staff. Do districts take advantage of this opportunity? In this paper, I test the hypothesis that school districts used school closures as an opportunity to re-allocate resources in the wake of serious declining funds caused by the Great Recession. My results do not show convincing evidence that districts induced to close a school from the Great Recession's budget shocks used the opportunity to re-orient staff. This could be for two reasons: (1) they are not realizing the opportunity they have or (2) they are already allocating resources efficiently and that is not affected by the change in educational setting. If the first reason is the reality, this suggests that districts did not respond optimally to the event of school closure.

CHAPTER ONE

INTRODUCTION

With the relatively short but extreme economic downturn brought on by the global Covid-19 pandemic, economists are identifying new lessons that can be learned by looking back at the Great Recession. During the recent pandemic, state funds began to follow similar trajectories to the 2008 recession.[1] Businesses closed and unemployment spiked, meaning income and sales tax – the main sources of state revenue – took a dive. Nationally, state funds make up about half of all funding for Kindergarten through grade 12 education. The economy is beginning to return to pre-pandemic levels, but it is not lost on us that the outcome for education spending could have been much worse. School districts have the opportunity to reduce spending by closing one or more schools, thereby decreasing expenditures on building maintenance and operation. This tool was leveraged by districts in the wake of serious declining funds caused by the Great Recession, but did the districts also use this event as an opportunity to re-allocate staff to be more efficient? In this paper, I test the hypothesis that school districts used school closures as an opportunity to re-allocate resources during modern history's worst economic decline. In general, I find no significant shifting of staff following a closure induced by the budget shock of the Great Recession.

The main question is "Do districts use school closure as an opportunity to re-allocate?" Reallocating staff resources inside a district is hard. Because of tenure, the teacher labor supply is not affected by market forces in the same way as other industries. Thus, it can be hard to change the staffing under normal circumstances. The Education Commission

[1] See https://www.cbpp.org/blog/projected-state-shortfalls-grow-as-economic-forecasts-worsen.

of the States (ECS) analyzed the legal reasons to fire a teacher in all fifty states plus DC. According to ECS, there is only one state – Arizona – where economic forces are a legal reason to lay off a teacher.[2] However, a dramatic change to the district environment, such as a school closure, can lower the barriers to letting teachers go and provide districts with the opportunity to re-allocate resources. In fact, most states allow teacher firing if there is a reduction in the number of teachers required. Closure reduces the number of teachers required both logistically (fewer teachers needed, just larger class size) and physically (fewer classrooms).

School closings offer opportunity for cost savings and for resource re-allocation. The frequency of school closures increased under the substantial financial distress of the Great Recession. The opportunity for re-allocation arises through the change in the number of teachers required. Beyond cost savings, these events can be a rare opportunity for districts to re-allocate their staff. According to economic theory, districts will re-allocate resources to be most efficient. If the district were already operating most efficiently, it will adjust its staff to reach the same level of efficiency in the new environment. If the district were not already operating most efficiently, it will use the closure as an opportunity to re-allocate resources to be most efficient; an otherwise very difficult task. The high barriers to re-arranging faculty imposed by tenure suggest that it is likely districts are facing a constraint that means they allocate resources inefficiently before the closure.

Why is the Great Recession a worthwhile context? In the past two years, states began spending more on Temporary Assistance to Needy Families (TANF) funds.[3] A very similar increase in state-funded programs drove the significant decrease in state education funding that made the Great Recession a standout event in education finance. It is possible that the same education funding cuts occur again, so studying impacts of the Great Recession in the

[2]See https://ecs.secure.force.com/mbdata/mbquestRTL?rep=TT05.

[3]See https://www.cbpp.org/research/family-income-support/states-must-continue-recent-momentum-to-further-improve-tanf-benefit.

education sector is a timely topic.

Few factors to education production that can be re-oriented like teachers. Teachers are in effect a choice variable of school districts, but only under certain conditions is it realistic to make significant changes to the number of teachers in the district. Recent research has shown that teacher quality is positively correlated with student performance. Given this, school districts would benefit from re-allocating resources such that higher quality teachers comprise a majority of the teachers on staff. Before we can estimate realistic benefits to this form of staff re-allocation, we need to understand whether districts are even choosing to re-allocate when given the opportunity. Because school closures provide such an opportunity, I examine whether districts choose to re-allocate when given the opportunity.

I use an exposure design to identify changes in staff resulting from recession-induced school closures. This method uses a district's reliance on state funding and changes in nation-wide reliance on state funding to predict which districts will close a school. I predict which schools will close based only on the recessionary budget shocks and estimate the effect of these closures on educational inputs. My results do not show convincing evidence that districts induced to close a school from budget shocks used the opportunity to re-allocate. This could be for two reasons: (1) they are not realizing the opportunity to re-allocate or (2) they are already allocating resources efficiently and that is not affected by the change in educational setting from the closure.

The outline of this thesis is as follows. In chapter 2 I discuss how a school closure occurs and the relevant literature on school closures, school finance, and the effect of the Great Recession on the education sector. In chapter 3, I discuss the theoretical framework and state the assumptions of this research. In chapter 4, I outline data sources used and provide descriptive statistics. In chapter 5, I describe the empirical strategy and discuss potential concerns. In chapter 6 I provide and discuss results, their relevance, and identification concerns. In chapter 7, I discuss this work's contribution to the economics field and its

implications for policy analysis.

CHAPTER TWO

BACKGROUND

After the United States experienced declining birth rates during the 1960s through the 1980s, school districts began closing schools more frequently. In the 1959 school year, there were 117,637 schools in 40,520 districts, but by 1979 those numbers decreased to 85,431 schools in 15,912 districts.[1] During the twenty year span, nearly 33,000 schools were closed and the U.S. went from having 2.9 schools per each district to 5.4 schools per district. As school closures became more frequent, a growing literature began examining their effect on students and the financial incentives driving the decision to close schools.[2]

There are many reasons for a school to be closed, but the main motivation is cost efficiency. Empirical research of economies of scale suggests that up to a school size of 5,000, it is less efficient to distribute a fixed education budget across multiple smaller schools than to spread that same budget across a smaller number of large schools (Andrews, Duncombe, and Yinger, 2002).

Spending efficiently became even more crucial post Great Recession when decreased tax revenue and increased demands for safety net programs caused an unprecedented decrease in state sources of K12 funding. As revenues fell, school districts addressed budget shortfalls by closing a higher frequency of schools. As a result, in the three years immediately following the Great Recession, at least seven percent of all U.S. school districts closed one or more schools each year, compared to the pre-recession value of four percent.

The literature on school closures has focused on two main topics: the decision to close

[1]Data are from Snyder (1993), table 20. These numbers do not differentiate between combined elementary/secondary schools.

[2]School district consolidation has also been studied, but is different from school closures due to the district remaining open after a closure, but at least one district closing during consolidation. For research on school district consolidation, see Engberg et al. (2012) and Jacques, Brorsen, and Richter (2000).

a school and the outcome of school closures. Diamond and Wright (1987) first explored the decision to consolidate schools inside a district. They attempt to develop an objective function that minimizes the tradeoff between efficiency and equity, but conclude that there is not a unique objective function to represent the views of educators, parents, students, administrators, and the general public. This inability to objectively model the decision to close schools has not yet been solved.

While there is not a sufficient objective function to identify schools that should be closed, the decision can be systematically organized and evaluated. There are five essential steps in closing a school: (1) gather facts, (2) decide which school to consider, (3) close the selected school(s), (4) make the transition, and (5) dispose of surplus property. Closing a school is potentially anguishing to a community, so the first thing done by the committee in charge is try to find other solutions. If closing a school is inevitable, the decision is announced as soon as it is made and usually does not come into effect before at least a year has passed.[3]

Sometimes districts do not have the choice to close, but are required by law. In 2004, Arkansas passed a law requiring all school districts with fewer than 350 students for two consecutive years to consolidate all schools within the district. In 2006, Ohio enacted a law which requires charter schools receiving a low performance score (determined by the state) for two of the three most recent school years to close permanently. Because states are making automatic closure laws, it is important to understand how closing a school affects its school district and whether districts are using the event as an opportunity to improve certain features, like resource allocation.

[3]These general guidelines are commonly cited by school districts making the decision to close a school across the country. See: https://www.cde.ca.gov/ls/fa/sf/schoolclose.asp

2.1 Monetary Costs and Benefits of Closure

To estimate whether a school will see positive cost savings on a per student basis, Dodson and Garrett (2004) implement a median voter model of education demand and find average per pupil cost savings of rural school consolidation. They find an average per-pupil cost decrease of 34% across rural public schools in Arkansas, and suggest that Arkansas could save $40 million annually by consolidating the schools in rural districts.

Schools benefit from cost savings and students benefit by moving to higher-performing schools (Duncombe, Miner, and Ruggiero (1995); Duncombe, Yinger, and Zhang (2016); Duncombe and Yinger (2007); Zimmer, DeBoer, and Hirth (2009); Andrews, Duncombe, and Yinger (2002)).

How does school district size affect closure? Kenny (1982) developed a model of economies of scale in school size that includes a "U-shaped" cost curve. The U-shaped cost curve was shown empirically by Ratcliffe, Riddle, and Yinger (1988) and Duncombe, Miner, and Ruggiero (1995) shortly after, and has been used in all models since.

Not all districts benefit from closure. Duncombe and Andrews's research shows that some schools are too large to see any significant gains from consolidation with another school. These long-term benefits usually outweigh the short-term costs of readjustment. Though the students readjust, there still is the potential for negative effects on students from being in a larger school and these effects can last even after adjusting to the new setting.

Research shows that as competition amongst schools in a district increases, each school becomes more efficient in its spending. Grosskopf et al. (1999) use a Herfindahl-Hirschman Index (HHI) to determine the concentration in local education markets and relate this to cost inefficiency. They empirically show that movement from an educational market with five schools with equal shares of market power to four schools is correlated with a 6-10% increase in allocative inefficiency. Gronberg et al. (2015) find similar allocative inefficiency

increases after school closure, and argue that economies of scale may not materialize due to inefficiencies introduced by reduced competition. This research relies on strict exogeneity in the decision to consolidate that may not be met. Karakaplan and Kutlu (2019) use the model from Gronberg et al. (2015) and control for endogeneity in school district achievement and education market concentration, finding even higher cost inefficiencies after decreasing the number of schools. Millimet and Collier (2008) study school districts in Illinois and find they become more efficient as other districts in the same county become more efficient regardless of the baseline level of efficiency in either district. Millimet and Collier (2008) attribute the effect to competition amongst schools, but make no conclusion about the impact of lessened competition. Failing to account for the relative inefficiency caused by decreasing the number of schools in a district through closure could lead to overestimation of the benefits of these actions (Gronberg et al., 2015).

The research surrounding the monetary costs and benefits to school closure are summarized in table 1.

2.2 Student Outcomes

Decreasing a school district's spending by closing a school comes at a cost. Several studies find a negative relationship between school size and student achievement (Archibald (2006); Bickel et al. (2001); Lee and Loeb (2000)). That is, larger schools seem to have diseconomies of scale with respect to student performance. Allcott et al. (2007) find that students in smaller schools have the benefit of closer relationships with their peers and that these relationships increase student performance and decrease misbehavior. Steinberg and MacDonald (2019) find that students are negatively affected by the readjustment following school closure, but that this disruption is temporary and fades after the first year. De Haan, Leuven, and Oosterbeek (2016) find no significant change in student performance from school closures.

Decreasing the number of schools weakens the competition inside school districts, but not all decreases in competition have definite negative effects. In 2004, Arkansas passed a law requiring all school districts which have less than 350 students for two consecutive years to consolidate all schools within the district. McGee, Mills, and Goldstein (2021) find null effects on student achievement in math and a modest increase of 0.08 standard deviations of the mean score on ELA standardized tests. Decreasing competition by eliminating the bad schools can have positive effects on students. Ohio enacted a law in 2006 which requires charter schools receiving a low performance score (determined by the state) for two of the three most recent school years to close permanently. Carlson and Lavertu (2016) find achievement gains of about 0.2-0.3 standard deviations, measured by standardized tests in math and reading. Brummet (2014) finds statistically significant positive effects of closing low-performing schools in Michigan for students leaving these schools. Beuchert et al. (2018) find that students show adverse effects across the board from school closures while Kirshner, Gaertner, and Pozzoboni (2010) find that minorities and students who were previously struggling in school are impacted more negatively by school disruption. Research on student effects are summarized in table 2.

2.3 Labor Outcomes

School personnel are affected by consolidation. Despite their importance to education production, there is a considerable gap in the literature focusing on a primary education input: teachers.

Natural disasters can provide an opportunity to study teacher mobility. Hurricane Katrina created a natural experiment to study the employment outcomes for teachers laid off as enrollment fell. The number of schools in the city dropped from 127 in 2004 to 78 in 2007, and the number of teaching positions was cut in half (Lincove, Barrett, and Strunk, 2018). During this same period, New Orleans public schools came under new management,

which dismissed all previous rules and regulations for teacher re-hiring. They refer to this as "the only existing case in which to study the consequences of a sudden removal of employment protections for an entire urban teacher market coupled with mass firing and selective rehiring" (p. 193). Using a multinomial logit model, they find that teachers who did not have tenure and teachers who were eligible for retirement were 17.2 and 13.2 percentage points less likely to return by 2007, respectively. In an earlier analysis, Lincove, Barrett, and Strunk (2017) find that teacher turnover rates for first-year teachers were higher than usual after the hurricane and turnover rates continued to rise until they reached a peak of 30% of first-year teachers in 2011; they attribute this to the different backgrounds between new teachers and those who were rehired.

Two papers study teacher employment outcomes after school closure using state-specific administrative data. The authors of both papers discuss the panel data only including teachers at public schools inside the state, causing teacher attrition to not be perfectly identified.[4] Hill and Jones (2021) use data from North Carolina to analyze the change in employment for teachers after school closure. Hill and Jones study school closure attributable to declining student enrollment in North Carolina, and they advise against extrapolating results to more general school closure settings. They report that six percent of teachers in North Carolina change schools in an average year, and in the year following a closure, teachers at the closed school are 77 percentage points more likely to change schools within their district and six percentage points more likely to leave the teaching profession. They find no significant effect on the probability of a teacher leaving to teach in a new district, to which they attribute the difficulty and disruption this would require. They conclude that the most experienced teachers are more likely to leave the teaching profession after being displaced by a school closure. Richards, Stroub, and Guthery (2020) study 15,000 teachers in

[4]For example, if a teacher moves to a private school or teaches in another state, this is coded as a teacher leaving the profession.

676 closed schools between 2003 and 2015 in Texas. They find that teachers who experience closure are 3.2 percentage points more likely to leave teaching and 2.3 percentage points more likely to begin teaching in a new district in the year following closure. They find that teachers with over 20 years of experience are four percentage points more likely to leave teaching and that black teachers are 6.5 percentage points more likely to leave teaching but do not explain why.

Teacher labor market research is summarized in Table 3.

2.4 Financial Impact on School Districts Due to The Great Recession

Recent studies have investigated the impact of the Great Recession on education finance. Evans, Schwab, and Wagner (2017) report the impact on school spending, employment, and class size from changes in state funding. Their results show that K12 employment decreased by 3.7 percent while teacher-student ratio increased by over five percent. Leachman and Mai (2014) find that 30 states operated on lower per pupil spending during 2013, and 14 states are spending less than 90 percent per pupil than their pre-Great Recession spending. Jackson, Wigger, and Xiong (2019) examine the impacts of the Great Recession on student achievement via school spending cuts and find that a reduction in school spending of ten percent causes a decrease in high school graduation rates of about 2.6 percentage points and decreases in test scores of about 0.079 standard deviations. Ju (2019) uses the Great Recession to study the causal impact of teacher unions on district finances and student achievement. He finds that an increase of one standard deviation in reliance on state revenue is associated with about 1.7 percentage points of additional decrease in per pupil spending.

The 2008 crash of the housing market had an extreme impact on state-reliant districts. It affected local and state taxes through property and property transfer tax revenues, sales tax revenues, and income tax revenue (Lutz, Molloy, and Shan, 2010). Of these channels, Lutz finds that property tax revenues were surprisingly resilient due to the long lags between

changes in market value and assessed value of properties. Because of this, the effects on state tax revenues was larger than the effect of local tax revenues. Local revenues are much different from state revenues. Evans, Schwab, and Wagner (2017) show that across all states, 79 percent of state revenues comes from income and sales taxes, while only 2 percent of state revenue comes from property taxes. They find that about 59 percent of local government tax revenue is funded through property tax and sales and income taxes produce about 20 percent of total revenues. These studies imply that a district that is more reliant on state revenues will see a larger funding decrease than a similar district which funds education mostly with local revenues. As is discussed in Evans, Schwab, and Wagner (2017) and Jackson, Wigger, and Xiong (2019), the effect of the Great Recession on state and local tax revenue was unlike any seen before.

The 2008 recession was the largest in the U.S. since the Great Depression. Between 2007 and 2009, real GDP and real per capita personal income fell by 3.1 and 8.3 percentage points, respectively. As this happened, safety net programs such as unemployment insurance and Medicaid, were used extensively. The national unemployment rate increased to 9.3 percent in 2009 from 4.6 percent in 2007 (Lutz, Molloy, and Shan, 2010). These safety net programs are meant to alleviate the financial pressure felt by local governments. Therefore, the Great Recession decreased state spending and increased federal spending disproportionately to local spending.

The Great Recession caused a re-prioritization of K12 funding. This sudden and extreme change to state spending caused state legislature to re-prioritize school funds to safety nets as observed in the decline in the state budget. The percentage of K12 education's budget decreased from 27 percent in pre-recession years to 23 percent post-recession. This is a result of safety net programs requiring more funds, and it suggests that K12 funding was being crowded out by welfare programs. This decrease in the share of state funds going to education implies that even if states were getting the same real income after the Great

Recession, the real amount of funding school districts receive would decrease (Evans, Schwab, and Wagner (2017); Jackson, Wigger, and Xiong (2019)).

Local revenue sources were more resilient to these funding impacts. Income and sales taxes were negatively affected by the recession, but property tax revenues increased for several years after. The reason for this is that property taxes are based on the assessed value of property (residential, commercial, business, and farm real property) and property tax rates. Local areas could raise property tax rates to offset declines in property values (Lutz, Molloy, and Shan, 2010; Alm, Buschman, and Sjoquist, 2011; Chakrabarti and Setren, 2011; Ihlanfeldt, 2011). Great Recession funding impacts can be explained by school district reliance on state revenues relative to local revenues. About 90 percent of all K12 funding in the U.S. comes from two sources: state revenues and local revenues and there is significant variation between state and local proportions of funds.

CHAPTER THREE

THEORETICAL FRAMEWORK

The decision of a district to close a school is based on its expected production and its budget constraint. When closing a school, a district is choosing to re-arrange its inputs to maximize educational production minus costs. The district does not focus only on monetary costs, but it also considers social costs in this decision. In this section I outline the objective function of a school district, discuss the conditions under which it will choose to close a school, and illustrate the mechanisms through which the Great Recession creates a natural experiment to study school closures.

3.1 Education Production

First, consider the objective function of the school district proposed by Lazear (2001):

$$p = f(M, T, A, B, g(\phi)) - c(M, T, A, B, h(\phi)) \tag{3.1}$$

where M is the number of students enrolled in the school, T is the number of full-time teachers, A is the number of full-time supporting staff, and B is the number of buildings in the district. $f : \mathbb{R}^{4+k} \to \mathbb{R}^+$ is a real-valued function of educational output and ϕ is a $1 \times k$ vector of other district-specific traits which affect the educational output according to the real-valued function $g : \mathbb{R}^k \to \mathbb{R}$, but are not affected by consolidation. School districts face a budget constraint determined by the cost function $c : \mathbb{R}^{4+k} \to \mathbb{R}^+$ that maps the inputs M, T, A, B, and ϕ to a single positive real number.

f represents total educational production, and following Lazear, it is not monotonically affected by either students (M), teachers (T), additional staff (A), or the number of buildings (B). This means that there is a maximum output to be attained by a specific combination

of these inputs, not just by increasing them indefinitely. Andrews, Duncombe, and Yinger (2002), in summarizing the economies of size literature, concludes that, like production, the first derivative of costs with respect to M is not monotonic either. The only inputs which are constantly increasing in their effect on c include T, A, and B. A summary of these effects is described in the first order conditions below:

$$\begin{aligned}
\frac{\partial p}{\partial M} &= \quad \frac{\partial f}{\partial M} \lesseqgtr 0 \qquad \frac{\partial c}{\partial M} \lesseqgtr 0 \\
\frac{\partial p}{\partial T} &= \quad \frac{\partial f}{\partial T} \lesseqgtr 0 \qquad \frac{\partial c}{\partial T} > 0 \\
\frac{\partial p}{\partial A} &= \quad \frac{\partial f}{\partial A} \lesseqgtr 0 \qquad \frac{\partial c}{\partial A} > 0 \\
\frac{\partial p}{\partial B} &= \quad \frac{\partial f}{\partial B} \lesseqgtr 0 \qquad \frac{\partial c}{\partial B} > 0
\end{aligned}$$

The goal of a school district is to maximize the value of p with respect to its controllable attributes and it can use closure as a mechanism to re-arrange the inputs in its schools. That is, it wants to find the values M^*, T^*, A^*, and B^* such that the following two conditions are satisfied:

$$\begin{aligned}
&\nabla p(M^*, T^*, A^*, B^*, g(\phi), h(\phi)) = 0 \\
&H\left[p(M^*, T^*, A^*, B^*, g(\phi), h(\phi))\right] \text{ is negative definite}
\end{aligned}$$

where $H[\cdot]$ represents the Hessian matrix. Therefore, understanding the shifts in inputs that occur after closure is important. Under normal circumstances, the inputs T and A are hard to change due to the difficulty in firing teachers who have tenure.

Most research seeks to estimate the impact that school closures have on f, using standardized test scores and value added techniques (Carlson and Lavertu (2016); Brummet (2014); Lee and Loeb (2000)). More recently, research has investigated the effect that a school closure has on teacher labor markets (Hill and Jones (2021); Richards, Stroub, and

Guthery (2020)). Because school closure decisions are made at a district/community level, understanding whether districts use the events to better allocate resources is important.

How do we analyze whether a closure had beneficial outcomes for the district? The ways which districts choose to manipulate B is unclear. For instance, one district may choose to close the most expensive building to operate, while another may choose to close the school that will cause the least disruption to students. In both of these cases B decreases, but we can imagine a third case where the district chooses to close one school and one building and open a new school in a new building in the next year; here B is unchanged.

The other inputs are likely to be changed after a closure to represent re-arrangement of resources. Let the updated inputs be denoted $\widetilde{M}$, $\widetilde{T}$, $\widetilde{A}$, and $\widetilde{B}$. The district's new production

$$\widetilde{p} = f(\widetilde{M}, \widetilde{T}, \widetilde{A}, \widetilde{B}, g(\phi)) - c(\widetilde{M}, \widetilde{T}, \widetilde{A}, \widetilde{B}, h(\phi))$$

may be higher or lower than initially. If $\widetilde{p} > p$, then the school closure will have had a net positive effect on production and it may conclude that the district is more productive after a recent school closure.

3.2 The Decision to Close

To illustrate why a district might choose to close a school, consider a district with just two schools, school A and school B. Assume schools A and B have enrollments of 2,000 and 3,000 students, respectively. School A has operating cost C_A and school B has operating cost C_B. Suppose that school A's building can accommodate 5,000 students if it increases its operating costs by ξ where $0 < \xi < C_B$. Then, consolidating schools A and B will allow the school district to accommodate all of its students at a cost of $C_A + \xi$, which is less than its current expenditures, $C_A + C_B$. In this situation, it is cost-efficient to consolidate the two schools into school A's building, and, ignoring social costs, the district will decide to do so.

In practice, the social costs to closing a school are frequently prohibitive (Kirshner, Gaertner, and Pozzoboni, 2010). There are many situations in which the district above would not close, though it is financially beneficial. That is because the district is not only considering monetary costs, but also the social costs of displacing students and teachers, decreased morale in staff, and potentially larger impacts on the community surrounding the school district. Thus, it does not consider just ξ, it must also consider the social cost μ, where $0 < \mu < \infty$. The school district will choose to consolidate schools if and only if $0 < \xi + \mu < C_B$.

3.3 Revenue Shocks in The Great Recession

The driving force in this paper's identification strategy relies on predicting the increased probability of experiencing closure from recession-induced funding shocks. I describe how differential exposure to a common funding shock can be used to identify school districts that were more seriously affected by the Great Recession. By identifying school districts that experience greater financial distress, I can predict an increased probability of the district decision to close a school (Hill and Jones (2021); Brummet (2014); Richards, Stroub, and Guthery (2020)).

School revenues come from three sources: local, state, and federal sources. Federal revenues make up only about 10 percent of K12 funding across all districts and there is not much variation across districts in the share of revenue that is federally funded (Evans, Schwab, and Wagner (2017); Jackson, Wigger, and Xiong (2019)), so I will only focus on local and state revenues in this section.[1] Consider a universe where district revenues come only from local and state sources. The revenue breakdown in this universe is expressed in equations 3.2 and 3.3 where *Property*, *Sales*, and *Corporate* represent revenues from

[1]This can be seen in the revenue source breakdown in figure 1.

property tax, sales tax, and corporate tax, respectively. α, β, and γ represent the share of local revenue that comes from property, sales, and corporate tax, such that $\alpha + \beta + \gamma = 1$. π, ρ, and τ are defined similarly for state revenues. The two revenue sources:

$$Local \equiv \alpha Property + \beta Sales + \gamma Corporate \tag{3.2}$$

$$State \equiv \pi Property + \rho Sales + \tau Corporate \tag{3.3}$$

Now, I make the claim that local revenues are *property-dependent*, meaning $\alpha > \beta + \gamma$; local revenues get a majority of their income from property tax. State revenues are *sales-dependent*, meaning $\rho > \pi + \tau$; state revenues get a majority of their income from sales tax (Evans, Schwab, and Wagner, 2017).

Suppose that before the Great Recession all revenue inputs are equivalent, that is $Property = Sales = Corporate = 1$. Then local and state revenues are equivalent before the Great Recession:

$$Local = \alpha + \beta + \gamma = \pi + \rho + \tau = State.$$

For simplicity, assume that the Great Recession does not affect property tax or corporate tax revenues, but it negatively affects sales tax.[2] Let $\widetilde{Sales}$ be the quantitiy of sales tax following the Great Recession, so $0 < \widetilde{Sales} < Sales$. Property and corporate taxes are still 1. Thus,

$$Local = \alpha + \beta\widetilde{Sales} + \gamma > \pi + \rho\widetilde{Sales} + \tau = State.$$

State revenues are smaller after the Great Recession because they were more dependent on sales tax.

[2]This assumption is fairly grounded in reality because empirical evidence has shown that the assessed values that property tax revenues are based on have a short-run elasticity less than 0.4. In fact, Evans, Schwab, and Wagner (2017) even shows that local property tax revenues increased for three years following the Great Recession.

Next I discuss how school districts are differentially affected depending on the main source of their revenue (local or state). Consider two school districts, A and B, that get all of their funding from either local sources or state sources. The share of district A's funding that comes from local sources is λ, and the share of its funding from state revenues is equal to $1-\lambda$. District B is the opposite of district A, the share of its funding from local sources is equal to $1-\lambda$ and the rest is funded by state revenues. For simplicity, assume local and state revenues are equivalent before the Great Recession ($Local = State$). This implies

$$A \equiv \big\{Local \times \lambda\big\} + \big\{State \times (1-\lambda)\big\} = \big\{Local \times (1-\lambda)\big\} + \big\{State \times \lambda\big\} \equiv B.$$

Let $0.5 < \lambda < 1$. Thus, district B gets the majority of its revenue from state sources and is more exposed to negative funding shock caused by the Great Recession. After the Great Recession, assume local revenues are unchanged, but state revenues decrease, so $\widetilde{State} < State$. The updated district revenues, $\widetilde{A}$ and $\widetilde{B}$, are

$$\widetilde{A} \equiv \big\{Local \times \lambda\big\} + \big\{\widetilde{State} \times (1-\lambda)\big\} > \big\{Local \times (1-\lambda)\big\} + \big\{\widetilde{State} \times \lambda\big\} \equiv \widetilde{B}$$

and district B is relatively more poor and more likely to close a school.

CHAPTER FOUR

DATA

The main analysis uses a collection of annually compiled data from the National Center for Education Statistics (NCES), the Annual Survey of School System Finances (ASSSF), and the Census Bureau. Data are available at the school, district, and county level for the sample period of 2001 - 2015.[1] The final dataset is a balanced panel of 43,438 schools and 6,955 school districts over fifteen years. A summary of data sources is reported in table 4.

This analysis uses a collection of education inputs as outcome variables. Data on enrollment, teacher staffing, instructional aides, guidance counselors, and library staff are available at the school-level and the district-level from NCES's Common Core of Data (CCD), which contains data for the entire public school universe recorded on October 1st of the corresponding school year. CCD data has a categorical variable each year for a school's status, with one of the values indicating that the school is closed. I create an indicator variable that is =1 if a school closes in a given year. I group the data by district and year and sum this indicator variable; if the sum is positive, I create a district indicator variable to indicate that district experienced a closure in that year.[2]

This paper also seeks to estimate the effect that school closure has on teacher mobility. For this, I include teacher-level indicators for whether a teacher leaves teaching profession and whether she transfers to a new school. Teacher-level data comes from NCES's Schools and Staffing Survey (SASS) and Teacher Followup Survey (TFS) which are sent to a random

[1] I use the convention that the school year is defined as the year in which the Fall semester occurs, e.g., the school year 2014 begins in Fall 2014 and ends in Spring 2015.

[2] The analysis in this paper depends on accuracy in identifying permanent school closure. There could be concern that schools are repeatedly showing up in the data as permanently closed. I report a count table on the number of times a school is 'closed' in the sample period in table 5. Less than 0.6 percent of schools in the raw data are closed more than once. For robustness, I run additional analyses in which I exclude the school districts which have one of these schools which closed more than once and find the results are not affected by this.

sample of public and private school teachers in the United States every four years.[3] Because SASS/TFS data is collected from a random cross-section every four years, a teacher who has been in the profession for twenty years has a higher probability of being surveyed than a teacher who is only in her third year of teaching. I bin teachers based on their experience into five groups: 1st year teachers, 2-5 years experience, 6-9 years experience, 10-19 years experience, and 20+ years to account for this length-based bias following Gilpin (2011). Appropriate weights are used in all analysis using SASS/TFS data. A summary of teacher-level variables is presented in table 6.

Because local area economic conditions are likely to be correlated with the employment outcomes, I include two controls for local economy at the county level. First, I include a median household income variable which comes from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program. Second, I include the county unemployment rate which I gather from the Census Bureau's Local Area Unemployment Statistics (LAUS) service.

Summary statistics for all school-level variables used in the analysis are presented in table 7 and summary statistics for all district-level variables are presented in table 8.

To ensure that I use representative data, I subset the merged raw data according to a set of rules. A district that only has one school at the beginning of the sample will be consolidating with a neighboring district when it closes its one and only school. Using these consolidating districts in my sample will cause models to estimate the effect of district consolidation along with school closure. The consolidation of school districts is not the subject of this paper, so I remove school districts that have only one school in the first year of the sample (2001). Doing this drops 1,257 districts from the sample. Gordon (2004) points out that financial data from ASSSF is noisy for extremely small districts. To account for

[3]The TFS is always sent to a subset of teachers who completed the SASS in the year prior. This analysis uses SASS years 2003, 2007, and 2011 and TFS years 2004, 2008, and 2012. Screenshots of SASS and TFS are shown in figures 4 and 5, respectively.

this, I follow Brunner, Hyman, and Ju (2020) and exclude districts whose total enrollment ever drops below 250 students during the sample window, removing 769 additional districts. A school district with zero teachers does not represent the general public school universe. To avoid including these districts in the sample, I drop districts that ever have less than 5 teachers during the sample period.[4] Imposing these rules on the sample drops a total of 2,067 districts from the original sample of 9,022. Thus, the final sample has $6,955 \times 15 = 104,325$ district-level observations.

The districts in this sample make up the schools that are in the school-level sample. Filtering on district-level enrollment and teacher employment does not fully exclude schools that have zero students or zero teachers – there still are schools that have zero students or teachers but the district sum is greater than 250 or 5 for students or teachers, respectively. To remove these from the school-level sample, I impose another rule that schools must have at least 50 students and 5 teachers in every year of the sample. These rules drop an additional 3,041 schools from the original sample of 46,479 schools. The final sample contains $43,438 \times 15 = 651,570$ school-level observations.

[4]There are special cases where retirement-centered communities will choose to create a school district with no intent to ever open a school or hire teachers. While these are valid observations, they do not represent the normal school district. See https://www.nytimes.com/2007/02/16/us/16scottsdale.html

CHAPTER FIVE

EMPIRICAL STRATEGY

This paper looks for re-arrangement of staff in a district following a school closure. Potential re-arrangement can be seen as increases or decreases in the number of staff in a particular role such as teaching or guidance. It also shows up in the form of teacher mobility as teachers leaving the profession or transferring outside the district. I investigate this by examining changes to teacher mobility and district staffing after a closure occurs within a district.

Table 9 provides descriptive statistics for these key educational inputs in the year before closure and the two years after. Comparing means at the district-level before and after school closures suggests that there is a large short-term increase in the number of teachers, instructional aides, library staff, and guidance counselors when a closure occurs.

It is unlikely, however, that these raw descriptive statistics reflect causal estimates. There are several factors that could be simultaneously impacting both the decision of a district to close a school and the employment of teachers and enrollment of students in the district. A main simultaneous effect being financial declines. Districts choose to close a school to alleviate both declining enrollment and financial stresses, but there is no universal rule to determine whether finances or student enrollment are more important in that decision (**engberg˙closing˙nodate**; Richards, Stroub, and Guthery (2020); Lee and Loeb (2000); Brummet (2014)). Thus, while declining enrollment or financial distress (both of which are observable) are usually present during a closure, it does not predict a future closure.

I use a difference-in-differences strategy to identify the average treatment effect of a district-level school closure decision on the allocation of district resources as they appear through staffing decisions. I find the effect of school closure by comparing the change in

the quantity of staff in districts when a closure occurs in a normal year to those districts that never close. The identifying assumption in this strategy is that had the closure never occurred, the difference between the treated average and the untreated average would remain constant relative to the year prior. Some school districts are more likely to close a school based on their setting and schools may have pedagogical reasons to prefer different amounts of various inputs.[1] Including two-way fixed effects controls for these unobservable factors. The district-level fixed effects controls for these preferences that remain constant across the panel. To control for state-level policies that may have occurred during the sample period, I include state-time trends in the analysis.[2] I estimate the linear model below using ordinary least squares (OLS)

$$y_{dcst} = \beta I(CLOSURE)_{dt} + \delta_d + \delta_t + (\phi_s \times t) + \psi \boldsymbol{X}_{ct} + \varepsilon_{dcst} \tag{5.1}$$

where district fixed effects δ_d control for the unobservable, time-invariant district characteristics for each district d, year fixed effects δ_t control for any bias potentially introduced through coincident policy changes in year t, and the district-specific error term is ε_{dcst}. The outcome y_{dcst} is either enrollment, teachers on payroll, or auxiliary staff in district d in county c in year t.[3] State-specific time trends $(\phi_s \times t)$ allow for comparing changes in a district's outcome relative to its own state's time trend. This is essentially including the natural-rate of changes to district staff for state s on the right-hand side of the equation. The matrix $\boldsymbol{X}_{ct}$ is a $n \times 2$ matrix of county-level economic controls including median household income and the county-level unemployment rate.

Given the complex decision process for deciding to close a school, school closures are

[1] McGee, Mills, and Goldstein (2021) and Smith and Zimmer (2022) both find this to be true for Arkansas school districts with respect to instructional aides and student-teacher ratio.

[2] For robustness, I run the model without including state-time trends. Results do not change.

[3] The district-level histograms of enrollment, teachers, and staff can be seen in figures 9, 10, and 11, respectively.

not likely to be randomly assigned conditional on just district and year fixed effects. There are simultaneous effects that increase the probability that a district will close one of its schools while decreasing the level of teacher employment in that district. Research has found negative relationships between student enrollment and teacher turnover (Boyd et al. (2005); Boyd et al. (2008)), and at the same time a decrease in the ability of smaller or low-performing school districts to attract teachers (Clotfelter et al., 2004). Thus, if a school district is exhibiting symptoms indicative of future school closure, its teachers and staff are possibly changing at the same time, implying reverse causality.

A key issue to identification is that districts that close a school and districts that do not close a school are different. Closures are a way to decrease spending on maintenance and operation, but not every school district makes that choice. Under typical circumstances, a school closes due to declining enrollment as well as budget constraints. Declining enrollment is related to the quantity of staff at the district: as fewer students are around, there are fewer teachers needed. So, when one teacher retires, the district is less concerned with immediately replacing that teacher's position at the school. This same situation applies to librarians and guidance counselors, and the schools have less demand for teacher aides. At the same time, research has found that staff shortages lead to school closures. This two-way effect creates an endogeneity concern with OLS regressions. For this reason, I use an instrumental variables (IV) approach.

To address the non-random assignment of school closure and to identify those districts which were induced to close a school in the wake of the Great Recession, I introduce an instrumental variable that uses a school district's reliance on state funding in 2008 to act as a plausibly exogenous source of variation in funding decreases that lead to closure. The instrumental variables strategy relies on the fact that school districts which were more reliant on state funding prior to the Great Recession were more likely to experience funding declines for reasons unrelated to the intensity of the recession or other policy changes that may have

occurred at that time. There are two reasons that this holds true. First, as the labor market worsened, demand for state-funded services including Medicaid and unemployment insurance increased (Moffitt, 2013). Prior to the Great Recession, states spent about 27% of their budgets on education, but this share fell to about 23% afterwards, resulting in a transferring of state funds away from education.[4] Second, greater reliance on state revenues is associated with deeper education funding declines due to tax bases. State taxes mostly consist of income and sales taxes while local taxes are mostly property tax (Evans, Schwab, and Wagner, 2017).[5] Holcombe and Sobel (1995) find that income and sales tax are highly elastic in the short-run. Conversely, property taxes are relatively inelastic in the short-run because taxes are collected on assessed values which follow considerable lag (Lutz, 2008). Also, local policy-makers often will offset declines in assessed property value by increasing the rate at which the properties are taxed (McMillen (2011); Lutz, Molloy, and Shan (2010)). This means state revenues are more sensitive to the business cycle and even without transferring state funds away from educatino, districts that relied more on state taxes would experience deeper budget declines.[6] Table 10 presents descriptive statistics on the quantity of school closures by dependence on state revenues.

I follow Goldsmith-Pinkham, Sorkin, and Swift (2020) in designing a shift-share experimental design using heterogeneous exposure to a common shock. The goal of this is to identify whether districts that had to close due to the Great Recession is also related to re-arrangements in staff. The 'shift' is the change in state funds for all districts in the U.S. relative to total revenue and the 'share' is the district share of state funds in 2008, the beginning of the Great Recession. I define the share parameter, W_d, as the share of school

[4]This pattern of transferring funds away from education is not unique to the Great Recession. Jackson, Wigger, and Xiong (2019) points out that it was observed during the early 2000s recession as well when the share of state spending on education fell from 29% pre-recession to 27% after.

[5]In fact, 79.9% of all state revenues were from sales and income tax while 59.3% of local tax revenues were from property taxes in 2012 (Evans, Schwab, and Wagner, 2017).

[6]Time series presented in figures 2 and 3 show the drastic decrease in total revenue and state revenue, respectively.

district d's revenue that came from state sources in 2008. This is meant to capture district d's exposure to negative funding shocks related to the Great Recession:

$$W_d = \frac{StateRevenue_{dt=2008}}{TotalRevenue_{dt=2008}}, \qquad 0 \leq W_d \leq 1 \tag{5.2}$$

Figure 6 shows that W_d is evenly distributed across the nation and figure 7 shows that the parameter follows an approximately normal distribution. In school districts that heavily rely on state revenues, the variable W_d will be closer to 1 while those which are less reliant will be closer to 0.

For example, Sheridan School District which is just west of Little Rock, AR in Saline County is very dependent on state funds: $W_{\text{Sheridan School District}} = 0.82$. Luther School District, which serves students from Oklahoma City, OK has a relatively low exposure to Great Recession funding shocks: $W_{\text{Luther School District}} = 0.17$. The growth in total revenue in these two school districts following the Great Recession illustrates the effect that exposure to the funding shocks has. The percent change in total revenue in Luther School District increased by 14 percent from 2008 to 2015 while the Sheridan School District's revenue increased only by 3 percent.

The shift parameter, V_t, is calculated along the same lines as W_d, but instead of fixing the year in 2008 and varying the district, I sum all revenues from all districts for a specific year t. Doing this picks up changes in the sample-wide share of revenue coming from state sources.

$$V_t = \frac{\sum_{d \in \mathcal{D}} StateRevenue_{dt}}{\sum_{d \in \mathcal{D}} TotalRevenue_{dt}}, \qquad 0 \leq V_t \leq 1 \tag{5.3}$$

where $\mathcal{D}$ is the set of all school districts d in the sample year t.[7] For example, the Great

[7]Due to the extremely large values that are being calculated in this shift variable, I choose not to calculate V_t using a "leave one out" method as removing one district's from the sum of all revenues in the entire sample is likely to have a negligible effect.

Recession caused the real state public school funds to decrease from $V_{2007} = 0.47$ in 2007 to $V_{2010} = 0.43$ by 2010. This reflects the nation-wide shock to state revenues relative to total revenues. The time series in figure 8 shows the dramatic downward shift in the share of K12 funding from state sources after the Great Recession.

I interact W_d and V_t to create a parameter that picks up variation in two dimensions. The first dimension is cross-sectional (introduced by W_d) and it compares school districts' reliance on state funds at the start of the Great Recession with each other – what the shift-share literature calls the "exposure." The second dimension is time (introduced by V_t) and it compares the makeup of K12 funding across time for the entire sample. Interacting W_d and V_t allows a comparison of school districts to each other and across time, and collapses the vector of $t = 15$ variables to just one instrument, permitting a just identified IV strategy.

$$Z_{dt} = W_d \times V_t, \qquad 0 \leq Z_{dt} \leq 1 \tag{5.4}$$

For Z_{dt} to be a valid instrument, I require that the shares of funding from state sources have no predictive power for school closures in the years before the Great Recession. That is, W_d should not be correlated with school closures before 2008. To test this, I interact W_d with a vector of year indicator variables (with 2008 removed). Regressing $I(CLOSURE)_{dt}$, on this vector of W_d interacted with year indicators estimates the explanatory power that the share of funding from state sources in 2008 has on the existence of a school closure in district d in year t.

$$I(CLOSURE)_{dcst} = \sum_{\substack{t=2001 \\ t \neq 2008}}^{2015} \beta_t (W_d \times t) + \delta_d + \delta_t + (\phi_s \times t) + \psi \boldsymbol{X}_{ct} + \varepsilon_{dcst} \tag{5.5}$$

To account for differences across districts and across time, I include district fixed effects δ_d and year fixed effects δ_t. To compare changes in each district's likelihood of closing a school

relative to its state's natural rate of closure, I include state-time trends ($\phi_s \times t$) and to account for local economic conditions, I include a matrix of county-level economic indicators $\boldsymbol{X}_{ct}$. I find the coefficients for β_t to be positive and statistically significant in years 2009, 2011, 2012, and 2013, but null results in the pre-recession years. The results of this trend test are reported in table 11 and figure 12.

Using Z_{dt} as an instrument, I account for the subset of school districts that are induced to close a school by the Great Recession's funding cuts. In order for the instrumental variable to be validly excluded, it should affect school staffing only through the existence of a predicted closure. I would not expect a school district to enroll more students or hire more staff because of the source of its funds. This is untestable, so I must make the assumption that the instrument only affects the outcomes throught its effect on the probability of school closure

Using Z_{dt} as an instrument, I estimate equations of the following form by Two Stage Least Squares (TSLS)

$$I(CLOSURE)_{dcst} = \gamma Z_{dt} + \delta_t^1 + \delta_s^1 + (\phi_s^1 \times t) + \psi^1 \boldsymbol{X}_{ct}^1 + \varepsilon_{dcst}^1 \qquad \text{First stage} \qquad (5.6)$$

$$y_{dcst} = \beta I(\widehat{CLOSURE})_{dt} + \delta_t^2 + \delta_s^2 + (\phi_s^2 \times t) + \psi^2 \boldsymbol{X}_{ct}^2 + \varepsilon_{dcst}^2 \qquad \text{Second stage} \qquad (5.7)$$

The endogenous treatment $I(CLOSURE)_{dt}$ is an indicator =1 if school district d closes a school in year t. y_{dcst} are the same outcome variables in the OLS model. To account for differences across districts, I include district fixed effects δ_d^1 and δ_d^2 in the first and second stage, respectively. δ_t^1 and δ_t^2 are year fixed effects in the first and second stage, respectively, and $(\phi_s^1 \times t)$ and $(\phi_s^2 \times t)$ are state-time trends allowing me to compare changes in the probability of closure or changes in the outcome variables in the first or second stage, respectively, to the natural rate of change in the state s. The coefficient γ is the effect of the shift-share variable on the probability of closure. The coefficient β is the causal effect that

a financial shock induced closure in district d in year t has on the outcome y_{dcst}.

A concern with the IV specification is colinearity between wealth and staff outcomes. It is possible that districts which receive a smaller share of their income from state sources are districts with more expensive property, so their local tax share will be higher. If funds were distributed uniformly across the state, this would be a natural effect. In fact, there is some correlation between median household income and a district's reliance on state funding. This might result in comparing "rich" and "poor" districts by comparing districts based on their reliance on state funding. At the same time, the outcome variables are weakly correlated with median household income. Including the economic controls and using district fixed effects should alleviate potential omitted variables bias.

CHAPTER SIX

RESULTS

There are three main outcomes I examine. First, I examine the effect of a school closure on school-level variables. The purpose of this is to find re-arrangements in the school environment. Next, I look at changes in the district-level arrangement of staff. Finally, I look for changes in teacher mobility in the presence of closure. These mobility outcomes are whether a teacher leaves the profession, transfers to a school within her district, or transfers to a school outside the district.

The benefit of using OLS methods is that it imposes weaker assumptions. When I use OLS to estimate the effect that closing a school has on resource allocation, I look at the effect of closing a school in that year has on the outcome in the same year. The benefit of this is that the coefficient is interpreted as the immediate effect that closing a school has on staff. A potential downside to this method is that OLS estimates may be biased by factors that affect both the likelihood that a district will close a school and the staff allocation in the school year. Districts which are underfunded will see declines in their enrollment and they will have a harder time replacing staff that retires or otherwise leaves the district. These districts are also more likely to close a school. By using OLS, I may be picking up the changes to enrollment and staff that are truly due to low funding in a school and attributing that to the event of school closure. If I interpret this as the true effect, I may be overstating the effect that a closure has on the outcomes.

In an attempt to address this potential overstating of effects, I use 2008 exposure to recessionary funding shocks as an instrument for school closure probability. Doing this estimates the changes to the probability of closure as being plausibly exogenous. Thus, I can potentially combat the problem of overstating the true effect of a closure discussed in the

previous paragraph. IV relies on stronger assumptions, however. In particular there is the "validly excluded" criterion. In this case, in order for the instrument to be validly excluded, a district's reliance on state funding in 2008 needs to have no effect on the outcome variable except for its increasing the probability of closure. There is not a test for this assumption at the time, so it should be kept in mind when discussing results.

First, consider the OLS results. By examining school-level effect, I attempt to answer the question "do districts attempt to put more teachers in schools relative to the number of students? These results are reported in table 13, and include school and year fixed effects. I find a small positive effect on the number of students in a school and no effect on the student-teacher ratio. The increase in student enrollment may be interpreted as the movement of displaced students to the surrounding schools within the district. Because the change is small in magnitude and because the ratio of students to teachers is not significantly affected by the event of a closure, despite the number of teachers remaining constant, it is possible that these increases in student enrollment is just noise.

By investigating district-level effects, I seek to find a re-orientation of resources done at a larger scale. School closures are one of a few opportunities that districts have where they can make large scale re-allocation decisions. The OLS results estimate a very small reduction of students. This might be interpreted as students leaving a district for one of the alternatives (different district, non-public alternative, etc.). There is a very small increase in the number of teachers relative to a district's average, but this effect is only significant when economic controls are included in the model. Due to the small magnitude of the effect and the fact that it is only significant when controlling for econonmic conditiosn, there does not seem to be a reliable estimate to the expected change in teacher staffing following a school closure. All other district-level staff variables are insignificant in the OLS models.

The results in table REF suggest that teacher mobility is not affected when a neighboring school in the district closes. Teachers leaving the profession or transferring

to a new school would be an effect of re-allocation, but I find no evidence to suggest this is at any rate different from the natural rate in years following a closure.

There is an important difference in the nature of the treatment variable in the OLS and the IV models. In the OLS model, the treatment (school closure) is binary, so the interpretation of the coefficient is the average treatment effect of the existence of a closure within a district. In the case of the IV model, the treatment is no longer binary. Instead, it is a continuous probability that represents the likelihood of a closure within a given district based on the Great Recession's impact on the district's budget constraint. This is due to the nature of the first stage equation. The first stage predicts the probability that district d experiences a closure in year t and the second stage estimates the affect of the predicted probability of such an event. Hence, the variable is no longer binary, but a continuous probability. As such, the coefficient on predicted closure in the IV specification is interpreted as the impact of a 0.01 increase in the probability of closure in district d in year t.

The school-level effect of recession-induced closures is estimated through IV and presented in table 16. Results are not significant for any of the outcomes. This might suggest that districts that chose to close a school in response to the financial distress put on them by the Great Recession did not use the opportunity to significantly change the staff or student-teacher ratio in individual schools. This might reflect a situation in which districts were too focused on preventing financial collapse to use the lowered barriers to rearrangement.

At the district-level, the IV results in table 17 also suggest no significant changes to district-level enrollment or teachers on staff. Taken in conjunction, this might suggest that adjusting the level of teachers on staff or enrollment was not at the forefront of districts' agenda when they chose to close a school. One result worth noting shows up in columns (3) and (6). The change in quantity of staff other than teachers increases by 2.9 percent. This increase is driven majorly by increases in the librarians on staff, which rises by about

3 percent. One story for this change in librarian staff could be that when districts close a school, they have a decrease in costs and they use this money to hire more librarians. Because these are recession-induced closures, however, it might be counterintuitive that a district would increase its staff when it is trying to alleviate financial pressures. A potential story to explain this is that individuals who would otherwise be given teaching positions are instead given jobs as library staff, but fulfill some of the roles that the district would utilize a teacher for. The reason this is plausible is that librarians have the same certifications as teachers, but a district may be able to pay librarians a lower wage.

It is important to note that in order for these IV results to be trustworthy, the instrument must be validly identified. This means that the instrument, 2008 reliance on state funds, affects the staff outcomes only through its affect on the probability that a district closes a school. If 2008 exposure affects staff outcomes through a different mechanism, results could be biased.

CHAPTER SEVEN

CONCLUSION

School closings are disruptive for students, parents, teachers, and their communities, and they are typically implemented as last resort solutions to declining enrollments and finances. Findings regarding the impact of closures on educational outcomes is mixed. Notably, the impact on student achievement varies greatly across settings (Brummet (2014); Carlson and Lavertu (2016); Gordon et al. (2018)). This paper instead sought to identify changes to key educational inputs: teachers and additional staff, a subject that just recently began receiving attention (Richards, Stroub, and Guthery (2020); Hill and Jones (2021)). Using a nationwide panel of data I find that, conditional on district and year fixed effects and controlling for local recessionary impact, school districts that were induced to close a school by Great Recession funding shocks increase their combined instructional aides, librarians, and guidance counselors by about 3 percent and there is no significant effect on teachers. The only significant results at the school-level are on enrollment and student-teacher ratios. In conjunction with no significant results on teacher mobility, this is evidence that districts are not making substantial re-orientations of their staff in the wake of a school closure, whether it is recession-induced or not.

The findings presented in this research suggest that there is no generalizable effect on teacher mobility resulting from a permanent closure within a district. This indicates that there is not a loss of trust or an increased propensity to leave a particular educational setting after the change. This is somewhat in contrast to the results of Hill and Richards. The null results this research finds is likely due to sample power of the SASS/TFS datasets. Due to data restrictions, identification of school closures is limited to the universe of public schools, and the probability that a teacher completes SASS and TFS in the year her district

experiences closure is quite small. Yet, with over 7,000 teacher-year observations, a large effect likely would be picked up, if one existed.

Kirshner, Gaertner, and Pozzoboni (2010) and Gordon et al. (2018) find that the disruption by school closure can plague students for years. Because of this, districts should take full advantage of the opportunity to re-arrange faculty. While it is possible that districts are already using resources as efficiently as possible before a closure, the high cost of teacher re-arrangement imposed by tenure implies that this is not the case. This research suggests that districts could be missing an opportunity to benefit their community as much as possible in the presence of an extremely disruptive event such as a school closure.

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APPENDICES

APPENDIX A

TABLES AND FIGURES

Table 1: Research Focusing on Candidacy for School Consolidation

Author (year)	Location	Contribution
Kenny (1982)	None; theoretical	As long as a school experiences positive economies of scale, it should continue to grow.
Ratcliffe et al. (1990)	Nebraska, USA	Schools that are either very large or very small benefit the most from consolidation.
Duncombe et al. (1995)	New York, USA	Schools that are either very large or very small benefit the most from consolidation.
Lee and Loeb (2000)	Chicago, USA	Teachers have better attitudes in smaller schools and there is, in general, a higher level of collective responsibility.
Andrews et al. (2002)	New York, USA	The optimal school district size is between 500 and 4,000.
Duncombe & Yinger (2007)	USA	Consolidation is beneficial for districts with a size between 300 and 1500
Zimmer et al. (2009)	USA	The upper limit to candidacy of consolidation is around 1.500 students

Table 2: Research Focusing on Student Outcomes Due to School Closure

Author (year)	Location	Contribution
Millimet & Collier (2008)	Illinois, USA	Districts in a county become more efficient as other districts within that county become more efficient.
Kirshner et al. (2010)	Redacted by request	Minority students and already low-performing students are most negatively affected by school closure.
Brummett (2014)	Michigan, USA	Students benefit from closing low-performing schools.
Gronberg et al. (2015)	Texas, USA	Monetary costs of inefficiency exist after consolidation, but students do not see any negative effects.
Carlson & Lavertu (2016)	Ohio, USA	Students benefit from having a law in place that automatically requires low-performing charter schools to close.
De Haan et al. (2016)	Denmark	No significant effects of school closure on students.
McGee et al. (2021)	Arkansas, USA	No effect or small positive effect on student performance after consolidation.

Table 3: Research Focusing on Labor Outcomes Due to School Closures

Author (year)	Location	Contribution
Lincove et al. (2018)	New Orleans, Louisiana, USA	Hurricane Katrina is correlated with a large and sustained medium-run increase in first-year turnover rates.
Hill and Jones (2018)	North Carolina, USA	Most teachers are able to find a new job teaching after being displaced by a closure, but it is harder for minority teachers. The most experienced teachers are most likely to leave.
Richards et al. (2020)	Texas, USA	Similar results Hill and Jones (2018).

Table 4: Data Sources

Variable Name	Data Source	Collection Frequency	Period
Teachers	NCES CCD	Annually	2001-2015
Enrollment	NCES CCD	Annually	2001-2015
Student-Teacher Ratio	NCES CCD	Annually	2001-2015
Instructional Aides	NCES CCD	Annually	2001-2015
Guidance Counselors	NCES CCD	Annually	2001-2015
Library Staff	NCES CCD	Annually	2001-2015
Leaves Profession	SASS, TFS	Every 4 years	2003, 2007, 2011
Transfer Within District	SASS, TFS	Every 4 years	2003, 2007, 2011
Transfer Outside District	SASS, TFS	Every 4 years	2003, 2007, 2011
Median HH Income	Census Bureau SAIPE	Annually	2001-2015
Unemployment Rate	Census Bureau LAUS	Annually	2001-2015

NOTE: This table summarizes the source, frequency, and time period of the outcome variables used in this analysis.

Table 5: Closure Count

	N				
	0	1	2	3	4
Count	106,313	32,756	630	30	3
Percentage of sample	76.1%	23.4%	0.5%	0.0%	0.0%

NOTE: Data from NCES CCD. This table reports the number of times a school in the sample is reported to be permanently closed.

Table 6: Occupational Status of Teachers in Sample

	Years of experience						
Outcome	0	1	2-5	6-9	10-19	20+	Sum
Left Profession	0.14%	0.67%	1.68%	1.17%	1.28%	2.98%	8%
Transfer Within District	0.06%	0.52%	1.45%	0.67%	0.59%	0.37%	4%
Transfer Outside District	0.09%	0.41%	1.17%	0.6%	0.93%	0.77%	4%
Total	0.98%	6.71%	21.57%	17.28%	26.61%	26.84%	100%

NOTE: Data comes from SASS/TFS. Together, teachers who have a value of 1 for any of the outcomes of interest combined make up 16 percent of the SASS/TFS sample. Minimum cell size contains 217 observations. Appropriate weights provided with SASS/TFS data are used in all analysis.

Table 7: School-Level Summary Statistics

	Mean	SD	Min	Max	N
Enrollment	583.0	433.0	50	5,491	652,000
Teachers	37.6	25.4	5	628	651,570
Student-Teacher Ratio	15.3	3.4	0.18	48.1	651,570
Has Closure	0.21	0.4	0	1	651,570
W_d	0.49	0.17	0.	0.99	651,570
V_t	0.46	0.02	0.43	0.49	651,570
Z_{dt}	0.23	0.08	0.	0.49	651,570
Median HH Income	54,435.4	14,969.0	21267.2	129429.1	651,570
Unemployment	6.3	2.4	1.1	26.3	651,570

NOTE: Data comes from NCES CCD and ASSSF. Summary statistics in this table summarize the district-level observations. i.e., the unit of observation is the school, so a mean enrollment of 377.5 implies that the average school in my sample has around 378 students.

Table 8: District-Level Summary Statistics

	Mean	SD	Min	Max	N
Enrollment	5,193.0	15,377.0	250	747,009	104,115
Teachers	315.9	870.4	7	36,115.2	104,115
Aides	72.3	204.1	0	15,321.0	87,480
Library Staff	9.7	22.8	0	648.0	48,240
Guidance Counselors	10.9	31.6	0	1,247.4	63,900
All Staff	90.2	205.3	0	5,814.0	31,200
Has Closure	0.09	0.29	0	1	104,115
W_d	0.54	0.16	0.01	0.99	104,115
V_t	0.46	0.02	0.43	0.49	104,115
Z_{dt}	0.25	0.08	0.	0.48	104,115
Median HH Income	51,455.5	13,468.0	21267.2	129429.1	104,115
Unemployment	6.7	2.7	1.1	28.9	104,115

NOTE: Data comes from NCES CCD and ASSSF. Summary statistics in this table summarize the district-level observations. i.e., the unit of observation is the school district, so a mean enrollment of 1,175 implies that the average district in my sample has 1,175 students.

Table 9: Descriptive Statistics Before and After Closure

	Unit of Observation	Enrollment	Teacher FTE	Student-Teacher Ratio	Instructional Aides	Library Staff	Guidance Counselors	All Staff
		7,589.147	453.69		102.508	14.357	15.814	123.667
Year Before Closure	District	(20,506.241)	(1,108.125)		(249.072)	(29.719)	(40.689)	(264.719)
		3,727	3,727		3,727	3,316	3,727	3,316
		15,560.467	940.813		204.178	25.488	32.337	249.771
No Closure	District	(40,917.426)	(2,267.266)		(544.663)	(51.492)	(79.599)	(470.979)
		3,727	3,727		3,727	3,316	3,727	3,316
		9,649.448	582.215		130.375	16.919	20.135	164.087
School Closure This Year	District	(23,261.215)	(1,314.77)		(313.535)	(32.711)	(49.681)	(302.291)
		3,727	3,727		3,727	3,316	3,727	3,316
		7,472.845	455.459		104.685	14.305	15.787	136.418
School Closure in Past 2 Years	District	(13,140.734)	(825.786)		(178.676)	(27.005)	(31.089)	(235.922)
		3,727	3,727		3,727	3,316	3,727	3,316
		658.07	40.944	15.975				
Year Before Closure	School	(465.297)	(26.461)	(3.659)				
		28,995	28,995	28,995				
		710.243	44.003	16.034				
No Closure	School	(487.679)	(27.055)	(3.47)				
		28,995	28,995	28,995				
		664.915	41.907	15.775				
School Closure This Year	School	(457.742)	(26.135)	(3.237)				
		28,995	28,995	28,995				
		637.709	40.587	15.673				
School Closure in Past 2 Years	School	(439.36)	(26.012)	(3.187)				
		28,995	28,995	28,995				

NOTE: Data are from NCES CCD. The mean is reported above the standard deviation (in parentheses) and the number of observations is reported below.

$$\begin{matrix} Mean \\ (Std.Dev.) \\ N \end{matrix}$$

Table 10: Percentage of School Districts That Experienced Permanent School Closure

Reliance on state funding (Quantile)	2001-2008	2009-2015	**Change**
First	7.11%	6.95%	**0.16 pp**
Second	8.14%	9.6%	**1.47 pp**
Third	8.16%	11.12%	**2.96 pp**
Fourth	6.28%	10.32%	**4.04 pp**

NOTE: Data comes from ASSSF. Reliance on state funding is calculated as the share of total district revenue that is coming from state sources.

Table 11: Test of Pre-Trends

	Existence of school closure
District Share × 2001	0.0177
	(0.0149)
District Share × 2002	-0.0103
	(0.0136)
District Share × 2003	-0.0250*
	(0.0145)
District Share × 2004	-0.0575**
	(0.0248)
District Share × 2005	-0.00511
	(0.0124)
District Share × 2006	-0.0167
	(0.0149)
District Share × 2007	-0.0112
	(0.0127)
District Share × 2009	0.0575***
	(0.0145)
District Share × 2010	-0.00331
	(0.0138)
District Share × 2011	0.0716***
	(0.0148)
District Share × 2012	0.126***
	(0.0161)
District Share × 2013	0.0683***
	(0.0145)
District Share × 2014	0.00952
	(0.0136)
District Share × 2015	0.00232
	(0.0126)
F(post-recession)	17.45
F(pre-recession)	2.574
N	209,954

NOTE: Data comes from NCES CCD. This is results of the trend test described in equation 5.5. The model includes school district and year fixed effects as well as district-level time trends and controls for county-level economic recession severity. Heteroskedasticity-robust standard errors clustered at the district level in parentheses.

Table 12: First Stage Results

	Z_{dt}			
Closure this year	2.254**	2.324**	-1.293***	-1.149***
	1.083	1.089	0.338	0.339
Unemployment		-0.001		-0.001**
		(0.001)		(0.000)
Median HH Income		0.006*		0.008***
		(0.003)		(0.001)
Level	School	School	District	District
N	401,895	401,895	104,115	104,115
F	4.33	3.94	14.63	29.81

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
All models include school and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 13: School-Level Results (IV)

	(1)	(2)	(3)
	ln(Enrollment)	**ln(Teachers)**	**Student-teacher ratio**
Closure	0.00655***	0.000773	0.0988***
	(0.001)	(0.002)	(0.033)
N schools	43,438	43,438	43,438
N	651,570	651,570	651,570

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
All models include district and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 14: District-Level Results (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Enrollment)	**ln(Teachers)**	**ln(All staff)**	**ln(Aides)**	**ln(Guidance)**	**ln(Library staff)**
Closure	-0.00633***	0.00284*	0.00173	-0.00156	-0.0004	0.005
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
N districts	6,941	6,941	6,265	5,832	4,266	3,216
N	104,115	104,115	31,200	87,480	63,990	48,240

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

All models include district and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 15: Teacher Mobility Outcomes (OLS)

	Leaves profession									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	0.018	0.024	0.012	0.009	0.033	0.035	-0.027**	-0.027***	0.004	0.004
	(0.021)	(0.024)	(0.030)	(0.027)	(0.030)	(0.028)	(0.010)	(0.010)	(0.020)	(0.021)
Unemployment		0.008		-0.006		0.007		0.003		-0.005
		(0.007)		(0.004)		(0.007)		(0.004)		(0.008)
Median HH Income		-0.001*		-0.001*		0.001		0.001*		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
	Transfer within district									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	0.082**	0.087**	0.034*	0.036*	0.015	0.015	0.008	0.008	0.023	0.022
	(0.037)	(0.037)	(0.018)	(0.020)	(0.012)	(0.013)	(0.011)	(0.011)	(0.014)	(0.013)
Unemployment		0.011		0.005		-0.003		-0.001		-0.001
		(0.010)		(0.005)		(0.003)		(0.002)		(0.002)
Median HH Income		-0.001		0.001		0.001		0.001		0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
	Transfer outside district									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	-0.034**	-0.032**	-0.035**	-0.0331*	-0.011	-0.011	0.003	0.004	-0.007	-0.006
	(0.014)	(0.015)	(0.017)	(0.017)	(0.012)	(0.012)	(0.006)	(0.006)	(0.008)	(0.008)
Unemployment		-0.005		0.006		-0.001		0.001		-0.001
		(0.003)		(0.006)		(0.005)		(0.003)		(0.001)
Median HH Income		-0.001*		0.001		0.001		-0.001**		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
N	1,360	1,360	1,410	1,410	970	970	1,440	1,440	1,970	1,970
N Schools	1,230	1,230	1,290	1,290	900	900	1,320	1,320	1,780	1,780

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Data comes from NCES CCD, ASSSF, and SASS/TFS. All specifications include state and year fixed effects, state-level time trends, and controls for county-level economic recession severity. Heteroskedasticity-robust standard errors clustered at the school level are reported underneath coefficients in parentheses. Data on teacher mobility are only available for years 2004, 2008, and 2012. Regression by groups estimated using ordinary least squares. The reported sample and subsample sizes are rounded to the nearest 10 as per license restrictions. Appropriate weights provided with SASS/TFS data are used in all analysis.

Table 16: School-Level Results (IV)

	(1)	(2)	(3)
	ln(Enrollment)	**ln(Teachers)**	**Student-teacher ratio**
Closure	-0.857	-0.645	-2.155
	(0.769)	(0.587)	(3.615)
N schools	43,438	43,438	43,438
N	651,570	651,570	651,570
F-stat (First Stage)	3.94	3.94	3.94

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

All models include district and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 17: District-Level Results (IV)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Enrollment)	**ln(Teachers)**	**ln(All staff)**	**ln(Aides)**	**ln(Guidance)**	**ln(Library staff)**
Closure	-2.637	4.445	2.964**	-8.491	-2.529	3.074**
	(3.666)	(4.182)	(1.355)	(8.85)	(4.445)	(1.351)
N districts	6,941	6,941	6,265	5,832	4,266	3,216
N	104,115	104,115	31,200	87,480	63,990	48,240
F-stat (First Stage)	29.81	29.81	19.03	29.68	26.66	20.66

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

All models include district and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 18: Teacher Mobility Outcomes (IV)

	Leaves profession									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	-0.081	0.062	-0.846	-0.555	0.032	-0.52	0.318	0.219	-0.61	-0.92
	(0.160)	(0.192)	(2.473)	(1.001)	(0.872)	(2.486)	(0.422)	(0.292)	(0.815)	(1.667)
Unemployment		0.008		-0.025		-0.005		0.003		-0.005
		(0.008)		(0.036)		(0.047)		(0.012)		(0.026)
Median HH Income		-0.001***		-0.001		0.001		0.001		0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
	Transfer within district									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	-0.332	-0.381	-0.29	-0.227	-0.273	-0.599	-0.088	-0.13	-0.142	-0.289
	(0.295)	(0.421)	(1.048)	(0.539)	(1.407)	(2.830)	(0.106)	(0.136)	(0.209)	(0.519)
Unemployment		0.002		-0.004		-0.015		-0.001		-0.001
		(0.015)		(0.018)		(0.051)		(0.006)		(0.009)
Median HH Income		0.001		-0.001		-0.001		0.001		0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
	Transfer outside district									
	1 year		2-5 years		6-9 years		20-19 years		20+ years	
Closure this year	-0.142	-0.104	-0.4	-0.189	0.051	-0.174	-0.193	-0.141	-0.106	-0.023
	(0.120)	(0.119)	(1.341)	(0.544)	(0.674)	(1.062)	(0.197)	(0.139)	(0.169)	(0.124)
Unemployment		-0.006		0.002		-0.005		0.001		-0.002
		(0.004)		(0.020)		(0.022)		(0.008)		(0.001)
Median HH Income		-0.001		-0.001		0.001		-0.001		-0.001
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
N	1,360	1,360	1,410	1,410	970	970	1,440	1,440	1,970	1,970
N Schools	1,230	1,230	1,290	1,290	900	900	1,320	1,320	1,780	1,780

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Data comes from NCES CCD, ASSSF, and SASS/TFS. All specifications include state and year fixed effects, state-level time trends, and controls for county-level economic recession severity. Heteroskedasticity-robust standard errors clustered at the school level are reported underneath coefficients in parentheses. Data on teacher mobility are only available for years 2004, 2008, and 2012. Regression by groups estimated using ordinary least squares. The reported sample and subsample sizes are rounded to the nearest 10 as per license restrictions. Appropriate weights provided with SASS/TFS data are used in all analysis.

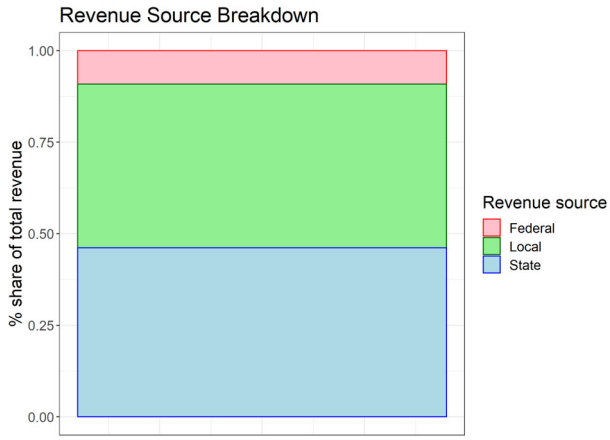


Figure 1: Data come from ASSSF. The bar chart above shows the breakdown of sample-wide revenues during the 2008-09 academic year. Federal funding makes up less than 10 percent of total revenues, so revenue is largely driven by state and local sources. Thus, we use the relative portion of revenue coming from state sources as a means to separate school districts.

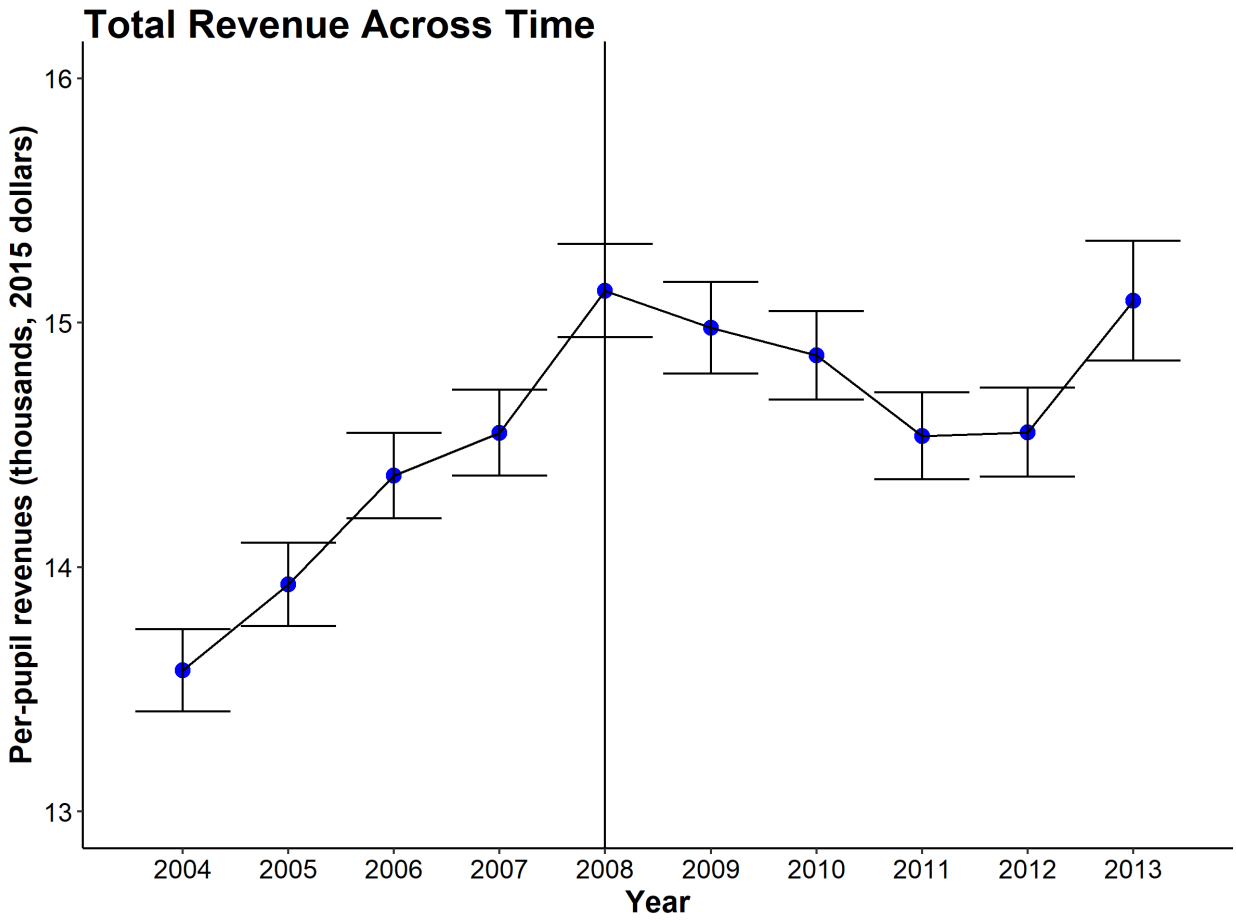


Figure 2: Data are from ASSSF. This time series shows the decrease in total per-pupil revenues that elementary and secondary education received following the Great Recession.

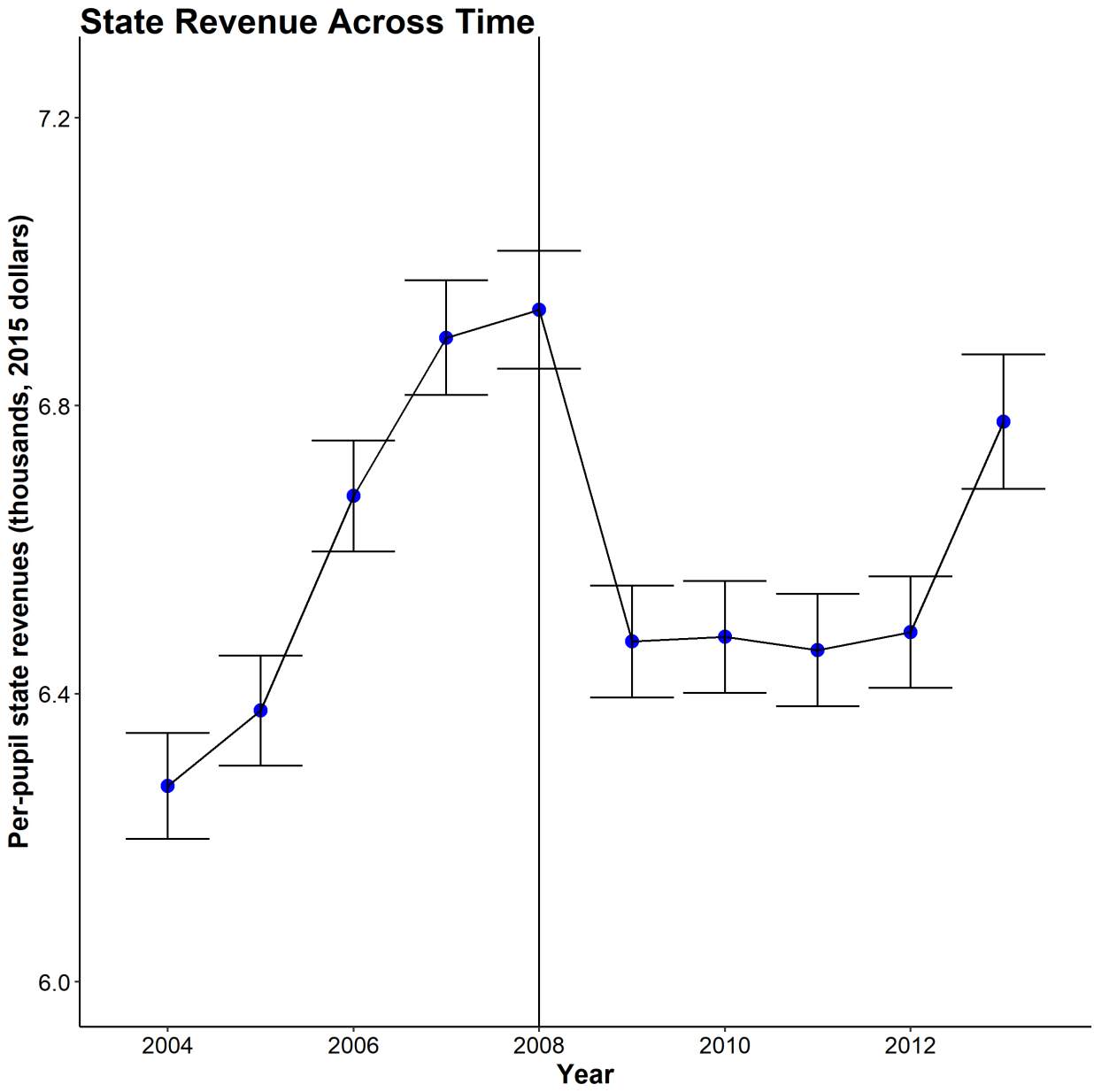


Figure 3: Data are from ASSSF. This time series shows the sharp decrease in per-pupil state funding received by K12 following the Great Recession.

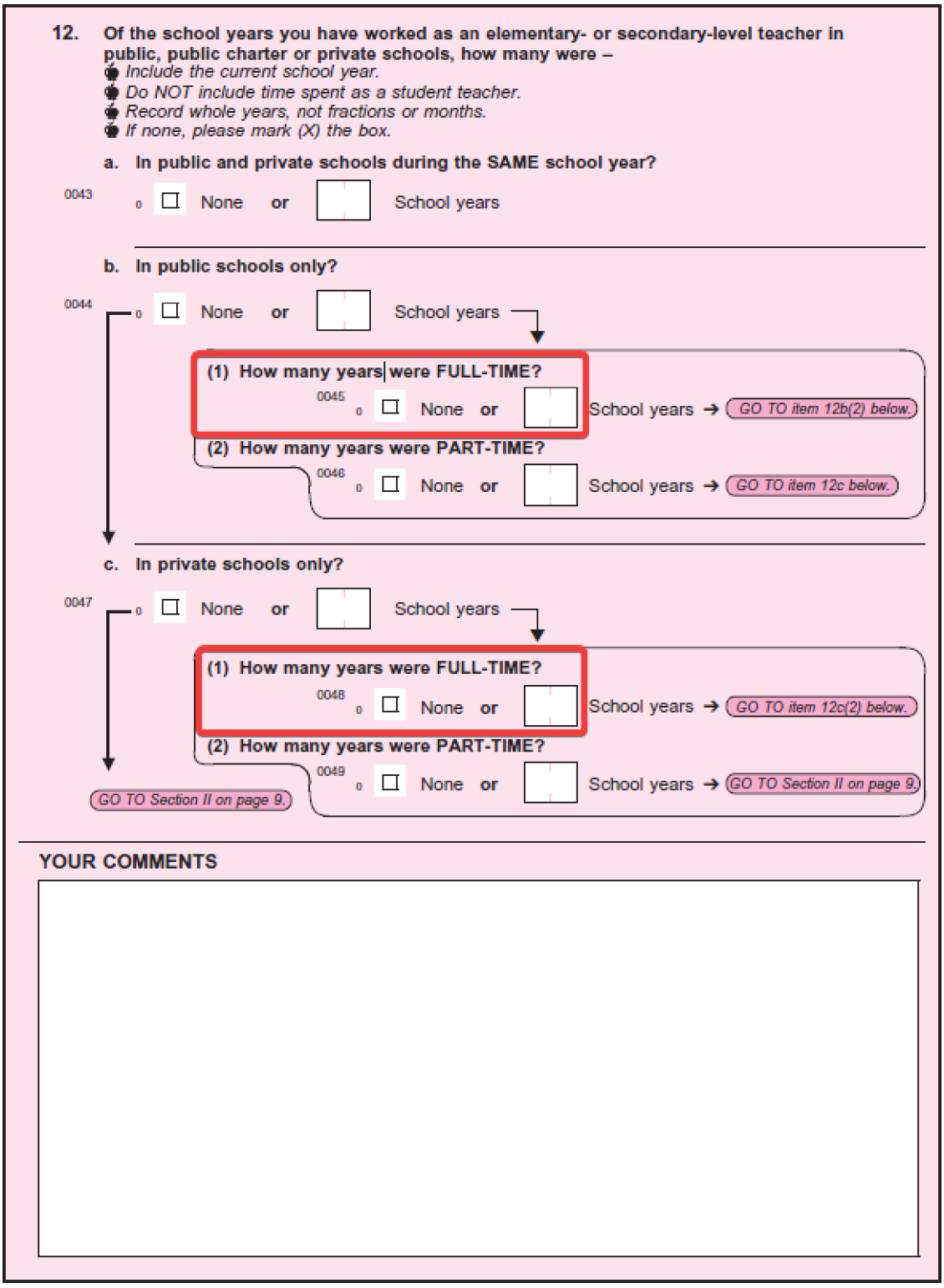
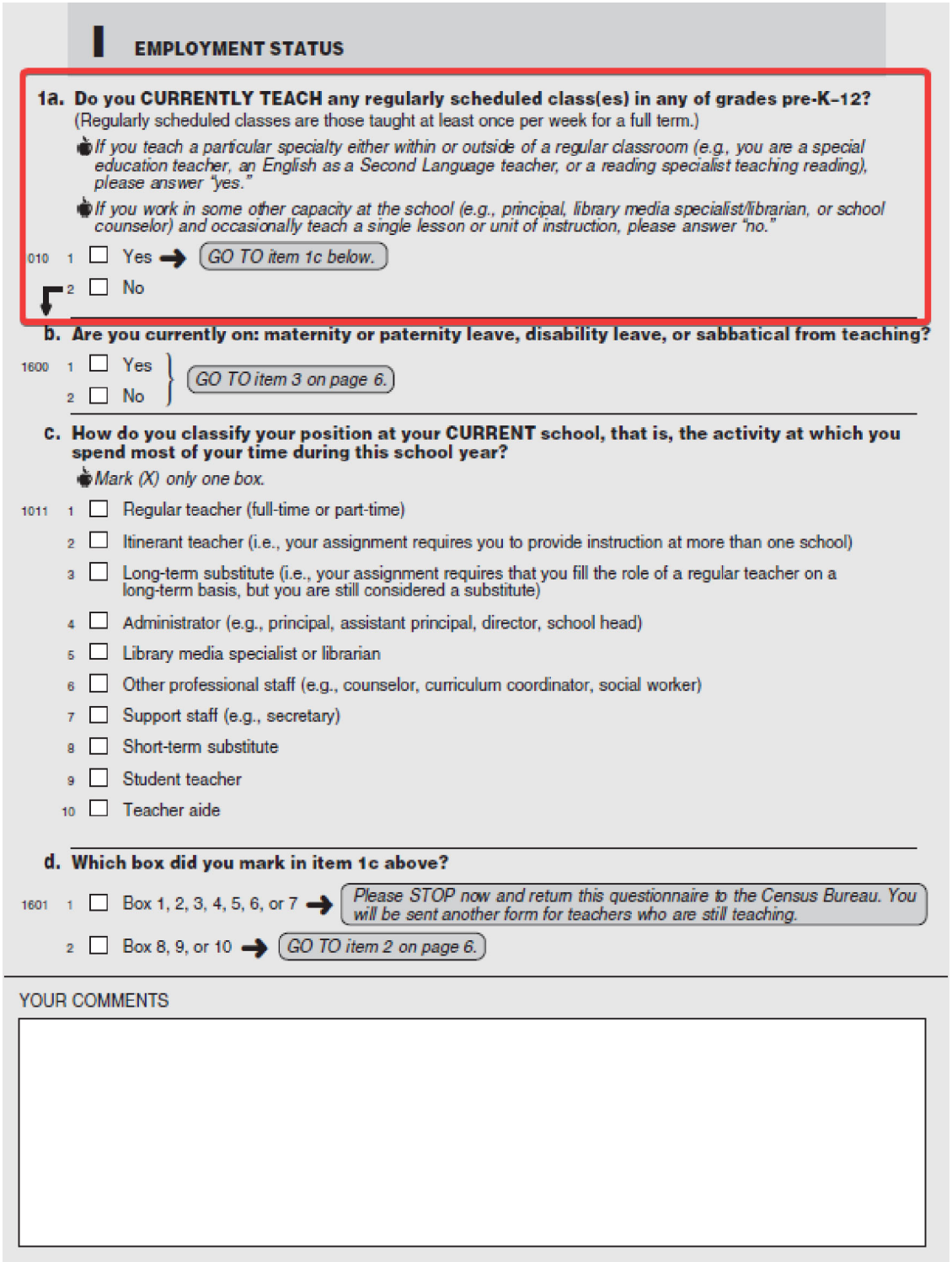


Figure 4: A screenshot of the 2011-12 AY Schools and Staffing Survey. I use the sum of the highlighted questions to calculate teacher experience.



EMPLOYMENT STATUS

1a. Do you CURRENTLY TEACH any regularly scheduled class(es) in any of grades pre-K–12?
(Regularly scheduled classes are those taught at least once per week for a full term.)

- *If you teach a particular specialty either within or outside of a regular classroom (e.g., you are a special education teacher, an English as a Second Language teacher, or a reading specialist teaching reading), please answer "yes."*
- *If you work in some other capacity at the school (e.g., principal, library media specialist/librarian, or school counselor) and occasionally teach a single lesson or unit of instruction, please answer "no."*

010 1 ☐ Yes → *GO TO item 1c below.*
2 ☐ No

b. Are you currently on: maternity or paternity leave, disability leave, or sabbatical from teaching?

1600 1 ☐ Yes
2 ☐ No
→ *GO TO item 3 on page 6.*

c. How do you classify your position at your CURRENT school, that is, the activity at which you spend most of your time during this school year?

- *Mark (X) only one box.*

1011 1 ☐ Regular teacher (full-time or part-time)
2 ☐ Itinerant teacher (i.e., your assignment requires you to provide instruction at more than one school)
3 ☐ Long-term substitute (i.e., your assignment requires that you fill the role of a regular teacher on a long-term basis, but you are still considered a substitute)
4 ☐ Administrator (e.g., principal, assistant principal, director, school head)
5 ☐ Library media specialist or librarian
6 ☐ Other professional staff (e.g., counselor, curriculum coordinator, social worker)
7 ☐ Support staff (e.g., secretary)
8 ☐ Short-term substitute
9 ☐ Student teacher
10 ☐ Teacher aide

d. Which box did you mark in item 1c above?

1601 1 ☐ Box 1, 2, 3, 4, 5, 6, or 7 → *Please STOP now and return this questionnaire to the Census Bureau. You will be sent another form for teachers who are still teaching.*
2 ☐ Box 8, 9, or 10 → *GO TO item 2 on page 6.*

YOUR COMMENTS

Figure 5: A screenshot of the 2012-13 AY Teacher Followup Survey. I use the highlighted variable to identify teachers who have left the teaching profession.

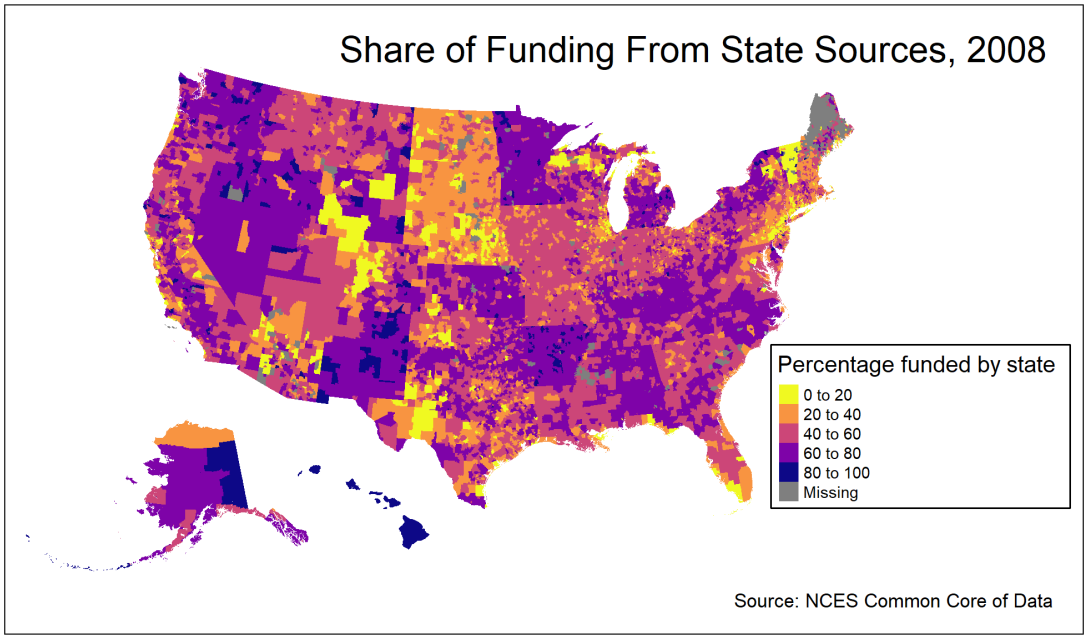


Figure 6: Source: NCES Common Core of Data. The values represent quintiles of the 2008 share of funding coming from state sources, W_d. Distribution across the sample appears to be uniform.

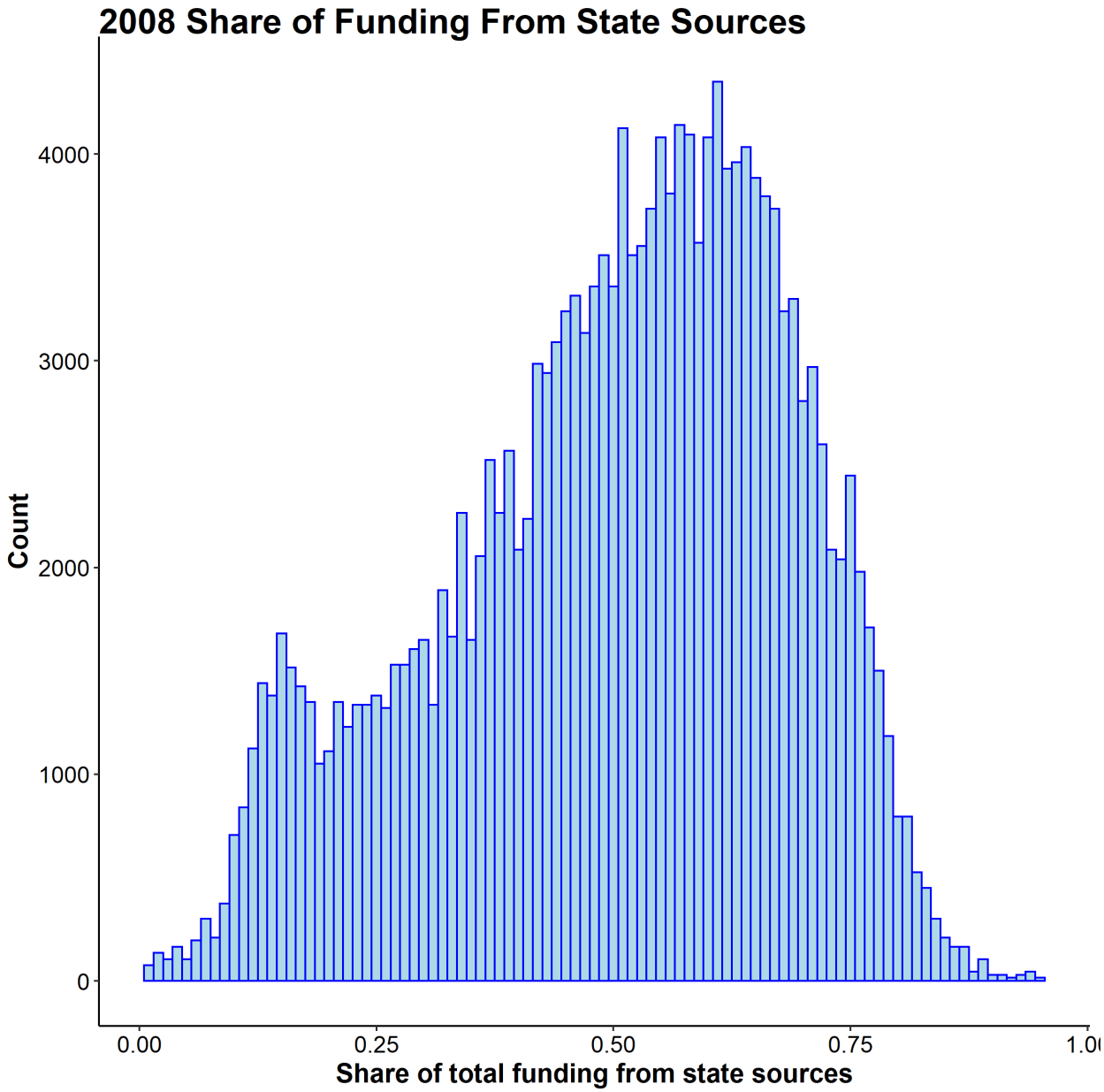


Figure 7: Data are from NCES CCD. This histogram shows the roughly normal distribution of exposure to negative funding shocks from the Great Recession.

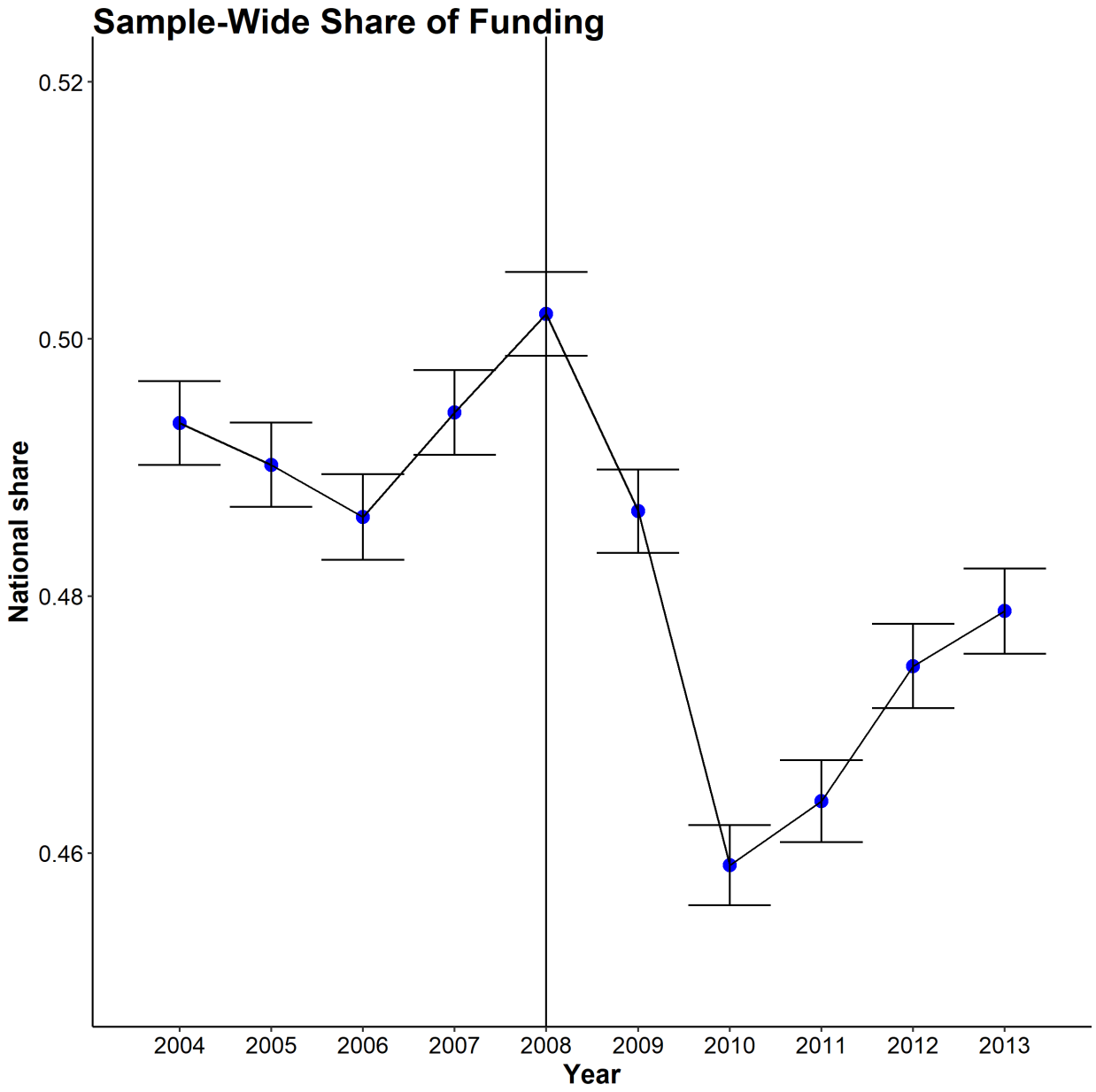
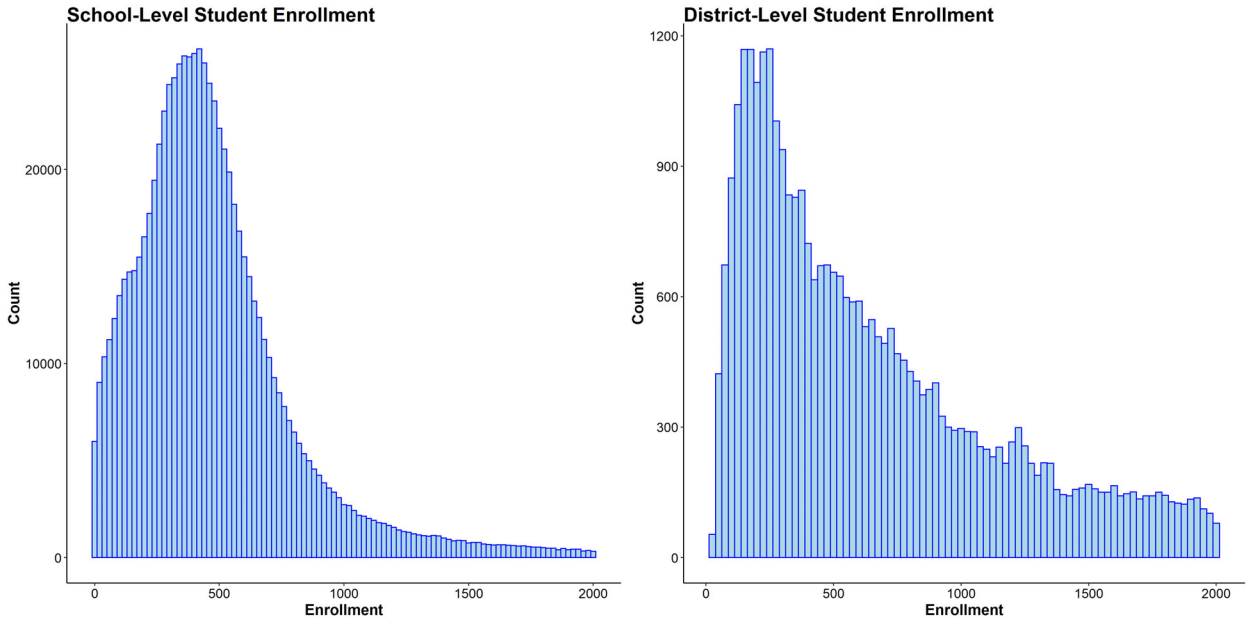
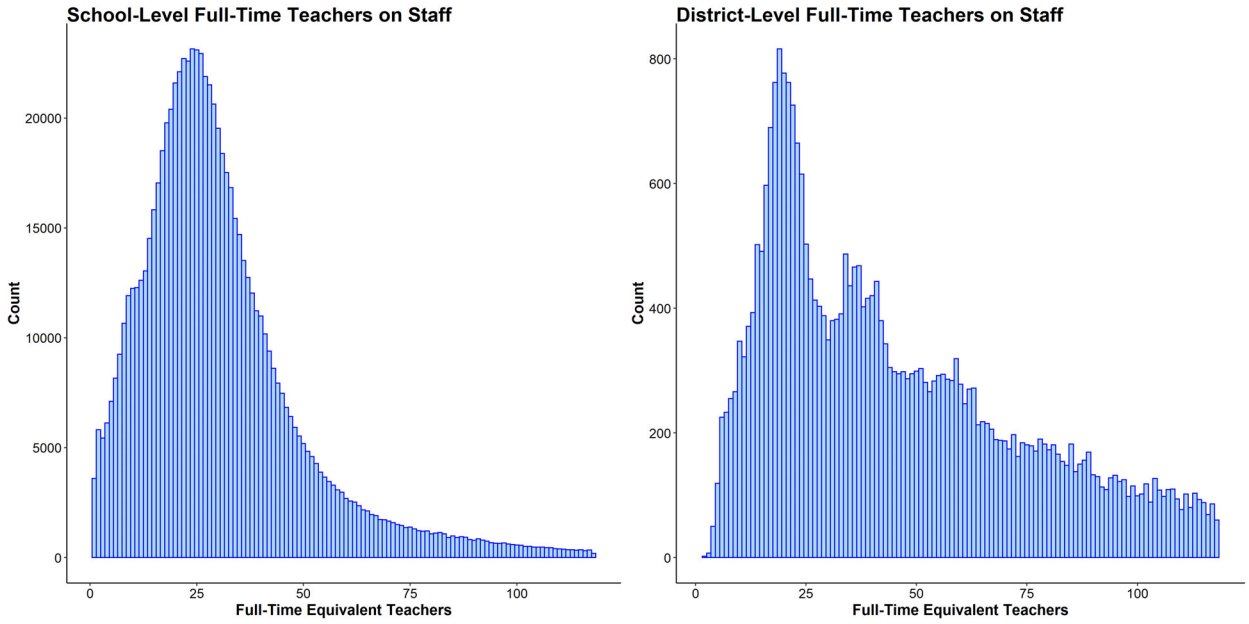


Figure 8: Data are from ASSSF. This time series shows the sharp negative trend in the share of K12 funding coming from state sources directly following the Great Recession.



(a) (b)

Figure 9: Data are from NCES CCD. These histograms show the distribution of student enrollment at the school and school district level.



(a) (b)

Figure 10: Data are from NCES CCD. These histograms show the distribution of teacher staffing at the school and school district level.

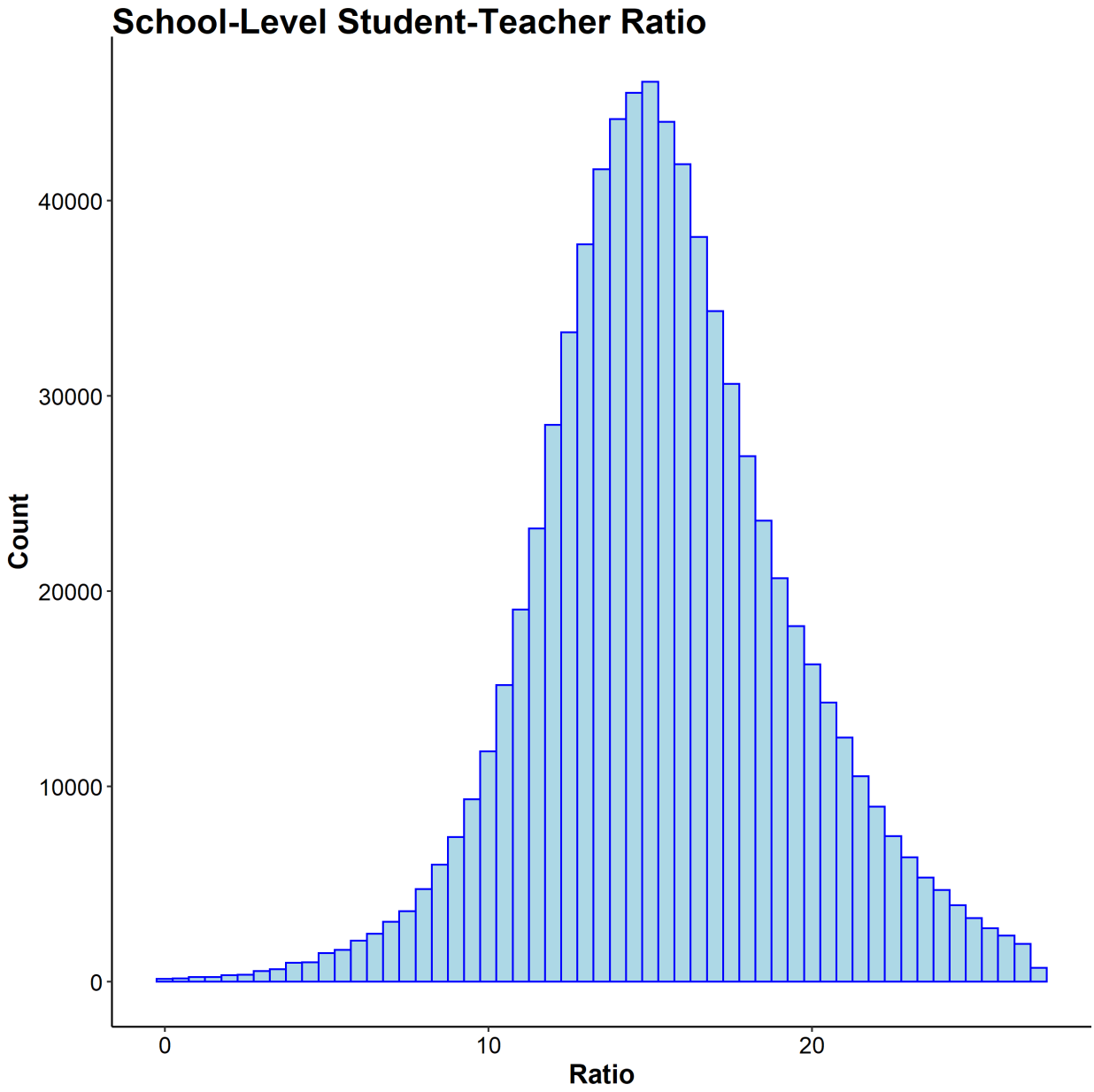


Figure 11: Data are from NCES CCD. This histogram shows the distribution of student-teacher ratios at the school level.

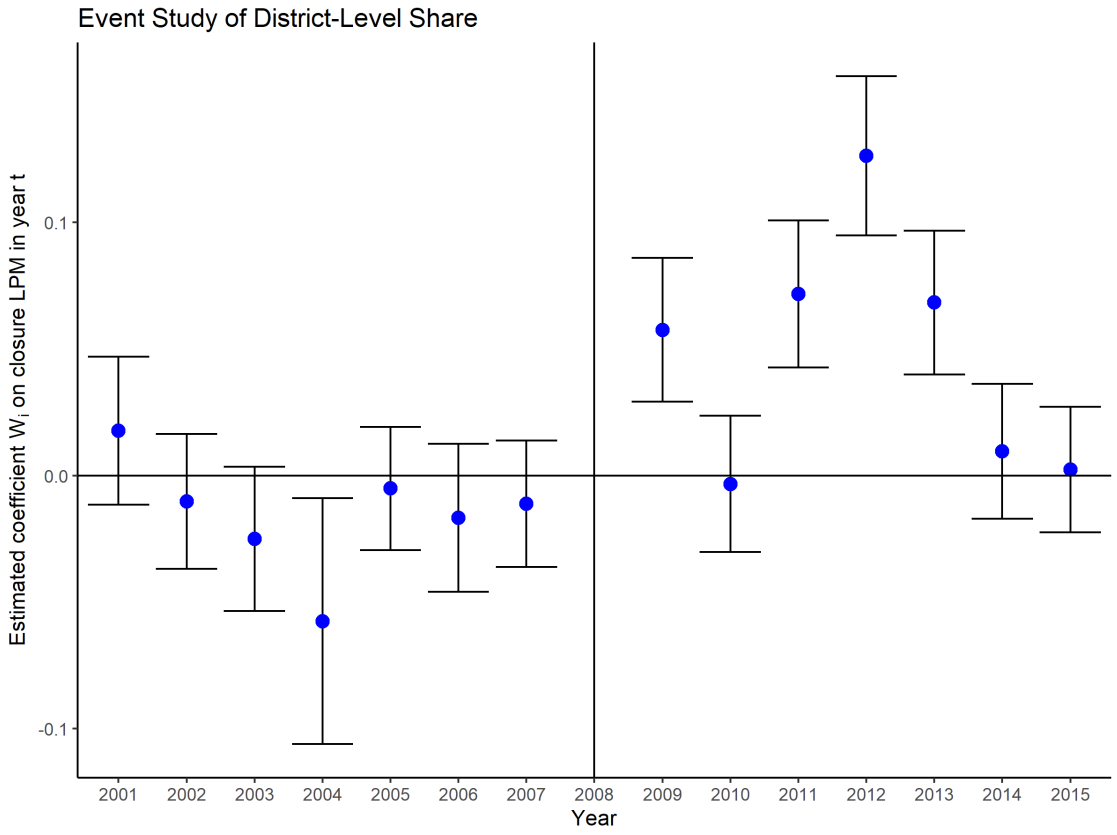


Figure 12: Source: NCES Common Cores of Data. Coefficient and 95% confidence intervals of coefficient on W_d when closure indicator variable is regressed on $W_d \times$ year dummies including district fixed effects and time trends, year fixed effects, and county-level predicted income and unemployment values.

APPENDIX B

TREATED DISTRICT RESULTS

To check robustness, I look at a specific subsample of the dataset. This subsample limits the observations to just the subset of districts which close one or more schools within the sample window. e.g., if a school district closes a school in 2010, it will be included in this group. I call this the "treated group." Treated group school summary statistics are presented in table 19 and treated group district summary statistics are presented in table 20. I find that the instrument loses some predictive power in this group. A potential cause for this decrease in predictive power in the first stage is removing districts which are less reliant on state funding that do not close. By using the instrument, I am only identifying a subset of treated school districts that close a school due to funding decreases following the Great Recession. Results do not change significantly when I use this subset as the analytic sample.

Table 19: School-Level Summary Statistics (Treated Group)

	Mean	SD	Min	Max	N
Enrollment	655.0	450.0	50	5,491	401,895
Teachers	41.3	25.8	5.00	628.0	401,895
Student-Teacher Ratio	15.8	3.3	0.18	48.1	401,895
Has Closure	0.3	0.46	0	1	401,895
W_d	0.49	0.15	0.02	0.99	401,895
V_t	0.46	0.02	0.43	0.49	401,895
Z_{dt}	0.23	0.07	0.01	0.48	401,895
Median HH Income	54,312.8	14,761.3	21,267.2	129,429.1	401,895
Unemployment	6.3	2.4	1.5	25.5	401,895

NOTE

Table 20: District-Level Summary Statistics (Treated Group)

	Mean	SD	Min	Max	N
Enrollment	7,372.0	19,764.0	250	747,009	60,045
Teachers	445.5	1,117.1	7	36,115.2	60,045
Aides	101.3	261.5	0	15,321.0	59,265
Library Staff	13.4	28.8	0	648.0	47,370
Guidance Counselors	15.4	40.6	0	1,247.4	58,200
All Staff	127.0	259.5	0	5,814.0	45,870
Has Closure	0.16	0.36	0	1	60,045
W_d	0.54	0.16	0.01	0.99	60,045
V_t	0.46	0.02	0.43	0.49	60,045
Z_{dt}	0.25	0.07	0.	0.48	60,045
Median HH Income	52,264.3	13,939.6	21267.2	129429.1	60,045
Unemployment	6.8	2.8	1.5	28.9	60,045

Table 21: School-Level Results (Treated Group)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ln(Enrollment)				**ln(Teachers)**				**Student-teacher ratio**			
Closure	0.00645***	0.00671***	0.477	0.536	0.000741	0.00101	0.721	0.844	0.102***	0.101***	-6.649	-7.840
	(0.001)	(0.001)	(0.904)	(1.03)	(0.002)	(0.002)	(1.334)	(1.588)	(0.035)	(0.035)	(12.97)	(15.54)
Unemployment		-0.00456***		-0.00833		-0.00405***		-0.0101		-0.00546		0.0511
		(799.0E-6)		(8.2E-3)		(984.0E-6)		(12.8E-3)		(13.9E-3)		(126.0E-3)
Median HH Income		0.00001**		0.00002		0.000014***		0.00003		-0.00007		-0.000215
		(496.0E-9)		(2.1E-6)		(525.0E-9)		(3.3E-6)		(8.4E-6)		(34.2E-6)
IV			X	X			X	X			X	X
N schools	26,793	26,793	26,793	26,793	26,793	26,793	26,793	26,793	26,793	26,793	26,793	26,793
N	401,895	401,895	401,895	401,895	401,895	401,895	401,895	401,895	401,895	401,895	401,895	401,895
F-stat (First Stage)			0.33	1.87			0.33	1.87			0.33	1.87

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

All models include school and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.

Table 22: District-Level Results (Treated Group)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ln(Enrollment)				**ln(Teachers)**				**ln(All staff)**			
Closure	-0.00614***	-0.00595***	1.860	1.258	0.00247	0.00256	2.561	1.774	0.00168	0.00188	1.521*	1.361*
	(1.5E-3)	(1.5E-3)	(2.0E+0)	(1.2E+0)	(1.7E-3)	(1.7E-3)	(2.6E+0)	(1.5E+0)	(3.5E-3)	(3.5E-3)	(870.0E-3)	(779.0E-3)
Unemployment		-0.00479***		-0.0171		-0.00483***		-0.0220		-0.00508**		-0.0215**
		(762.0E-6)		(12.0E-3)		(824.0E-6)		(15.2E-3)		(2.1E-3)		(9.9E-3)
Median HH Income		-0.000002***		0.000007		-0.00003***		0.000001		-0.000002		0.000002
		(646.0E-9)		(2.6E-6)		(576.0E-9)		(3.2E-6)		(1.1E-6)		(2.6E-6)
IV			X	X			X	X			X	X
N districts	4,003	4,003	4,003	4,003	4,003	4,003	4,003	4,003	3,058	3,058	3,058	3,058
N	60,045	60,045	60,045	60,045	60,045	60,045	60,045	60,045	45,870	45,870	45,870	45,870
F-stat (First Stage)			1.05	15.3			1.05	15.3			1.43	15.71

NOTE: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

All models include school and year fixed effects. Heteroskedasticity-robust standard errors are clustered at the district level and reported below coefficients in parentheses.