Beyond Spending Levels: Revenue Uncertainty and the Performance of Local Governments*

Stéphane Lavertu†
John Glenn College of Public Affairs
The Ohio State University
1810 College Rd., 110 Page Hall
Columbus, OH 43210
lavertu.1@osu.edu

Travis St. Clair
Wagner School of Public Service
New York University
295 Lafayette Street
New York, NY 10012
mts15@nyu.edu

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Abstract

Revenue uncertainty is a common concern among public administrators, but little research examines its effects on service delivery. Using a novel empirical strategy to capture how revenues deviate from administrators' expectations, we estimate the impact of revenue uncertainty on Ohio public school districts' educational effectiveness. We find that errors in districts' revenue forecasts can have a significant negative impact on student achievement, beyond what one would expect based on changes in spending levels. In particular, a one percentage point increase in error involving revenue shortfalls can lead to declines in student achievement growth of up to 0.02 standard deviations during the following school year, which equates to about 8 days' worth of learning. These effects are concentrated in large, non-rural school districts with relatively low fund balances.

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†Corresponding author

1 Introduction

U.S. state and local governments increasingly struggle to manage their finances amidst fluctuating revenues and economic uncertainty.[1] Research documents how these governments adjust their patterns of taxation and spending following unanticipated revenue declines,[2] but we know little about revenue uncertainty's impact on service delivery. Estimating the magnitude of such an impact could help researchers identify opportunities to enhance the performance of public organizations—and the multitude of programs they administer—without increasing public spending. We examine whether there are such opportunities for performance improvements in the context of U.S. public education. Whereas researchers have examined the impact of school district fiscal stress (e.g., see Downes and Figlio, 2015) and increased spending levels (e.g., Jackson, Johnson, and Persico, 2015; Lafortune, Rothstein, and Schanzenbach, 2016) on student achievement, to our knowledge we are the first to consider the specific impact of revenue uncertainty on educational delivery.[3]

Revenue uncertainty is a serious concern among school district administrators who wish to engage in strategic planning.[4] There is evidence that districts grow their cash balances to deal with the uncertainty associated with state and federal sources of revenue (Ványolós, 2005), but school districts are often unable to build sufficient reserves due to political constraints,[5] rapidly rising costs, and the structure of teacher labor contracts (e.g., see Roza, 2013). Thus, they are likely to respond to shortfalls either by raising more local revenues

[1] For example, see Lav, McNichol, and Zahradnik (2005) and Behn and Keating (2005).

[2] Poterba's (1994) paper is a seminal study examining states' abilities to respond to fiscal stress. See Cromwell and Ihlanfeldt (2015) for a more recent study and review of this research at the local level. For a focus on schools, see Chakrabarti, Livingston, and Roy (2014) and Hall and Koumpias (2016), for example.

[3] Impacts on achievement could be quite consequential, as student achievement in math and reading has been linked to superior labor market outcomes (Chetty, Friedman, and Rockoff 2014a) and economic growth (Hanushek and Kimko 2000; Hanushek 2011).

[4] According to Loeb, Bryk, and Hanushek (2008, pages 17-18), in California "Over three quarters of superintendents surveyed thought that knowing the [state] budget earlier in the year would be either a great deal of help or essential for them to improve outcomes for students (Loeb, 2007/GDTF)." Some research also suggests that having a predictable revenue stream, as opposed to district wealth, best explains whether districts employ rational planning and evaluation processes in budgetary decision-making (Sielke, 1996).

[5] Voters may be less inclined to approve tax levies if districts have significant fund balances. Additionally, although districts and state governments often have rules in place that require minimum balances, state lawmakers have been known to discourage reserves they deem to be too large.

(Reschovsky, 2004; Dye and Reschovsky, 2008; Alm and Sjoquist, 2009; Alm, Buschman, and Sjoquist, 2009; Chakrabarti, Livingston, and Roy, 2014) or immediate cost-cutting, which has been linked to teacher dismissals and lower student achievement (e.g., see Berne and Stiefel, 1993; Figlio, 1997; Nguyen-Hoang, 2010; Kogan, Lavertu, and Peskowitz, 2017).[6] State limits on the authority of districts to raise local revenues (Downes and Figlio, 1999) and an unwillingness among voters to raise taxes during hard financial times make cost-cutting particularly likely.[7]

Even if the link between per-pupil spending and student achievement were negligible (e.g., see Hanushek 2006), revenue shortfalls that have a minor impact on spending could nonetheless affect student learning. For example, revenue shortfalls related to the Great Recession led to turnover even among teachers who were not targeted for layoffs (Goldhaber, Strunk, Brown, and Knight, 2016), and teacher mobility between grades or schools—"teacher churn"—can have a significant negative impact on student achievement (Atteberry, Loeb, and Wyckoff, 2016; Ronfeldt, Loeb, and Wyckoff, 2013; but see Adnot, Dee, and Wyckoff, 2016). These findings are also consistent with public administration research documenting the deleterious effects of budget cuts—both when they are proposed and after they are implemented—on employee attitudes and behaviors (e.g., see Keifer et al., 2015). In other words, the mere possibility of expenditure cuts may affect student learning due to its impact on personnel.

Efforts to raise funds in response to shortfalls can also be disruptive. For example, districts with the authority to raise operating revenues through tax levies may need to engage in costly political campaigns to secure voter approval. There may be direct financial costs related to administering the election, as well as the reallocation of effort among both administrators and teachers in support of the tax referendum. Uncertainty over the levy

[6]District spending cuts disproportionately target less essential services, but teachers are districts' largest obligation by far and cuts to instructional spending are common (e.g., Berne and Stiefel, 1993; Figlio, 1998; Figlio and O'Sullivan, 2001; Kogan, Lavertu, and Peskowitz, 2017).

[7]Some researchers suggest that revenue-raising is more likely to be a long-term strategy as opposed to a way of immediately addressing shortfalls (MacManus, 1993).

outcome also could affect employee morale for an extended period—whether or not the tax levy ultimately gains voter approval. Other types of fund raising—such as soliciting donations, implementing fees, or seeking relief from higher-level governments—may have similarly disruptive effects.

Finally, deficits or low fund balances may affect government credit ratings and invite political scrutiny. For example, many states have financial intervention systems in place for school districts that run deficits (see Thompson, 2016). The administrative requirements of these interventions—such as strategic planning and reporting requirements—could be quite disruptive, beyond the cost-cutting and revenue-raising they might require.

Thus, sudden administrative disruptions due to the realization of lower-than-expected revenue could have impacts on educational delivery that are more pronounced than one would expect based on the corresponding changes in spending levels. We estimate the effects of such revenue uncertainty on school district service delivery using official revenue forecasts of Ohio school districts from 2008 to 2016. The state requires its 611 school districts to submit five-year forecasts of future revenues in autumn and spring of every year. The spring forecasts provide us with what are ostensibly districts' expectations regarding revenues in the upcoming school year. However, districts may strategically manipulate their official forecasts to convince stakeholders—particularly residents who must approve tax levies and state policy-makers who regularly tinker with state funding formulas—that they need more money or that their finances are sound.[8] Additionally, forecast error may be an endogenous predictor of school district performance. For example, a district's managerial competence may be correlated with both its propensity to make forecasting errors and its effectiveness at educating students. Consequently, examining the link between errors in official forecasts and district performance would confound the impact of true errors due to revenue shocks with errors due to manipulation or a lack of administrator skill.

[8]Research has highlighted the importance of political acceptance and bargaining in revenue forecasts (Mikesell and Ross, 2014; Nutt, 2006), which is consistent with a larger body of work that stresses the role of political concerns in the strategies of budget analysts (e.g., see Willoughby and Finn, 1996).

To address these concerns, we use panel methods and an instrumental variables approach to isolate the impact of errors in districts' official revenue forecasts that reflect true errors in district beliefs. Specifically, we instrument for forecast error using revenue deviations from three-year trends, which are baseline data points the state encourages districts to consider when forecasting future revenues. Using two-stage-least squares (2SLS) models with district fixed effects, we estimate the impact of this shock-induced forecast error on annual "value added" estimates of district educational quality, as captured by student test score gains in math and reading. The primary identifying assumption is that, conditional on district fixed effects (such as administrative skill)—as well as a number of time-varying factors such as annual per-pupil expenditures—revenue deviations have no immediate, measurable impact on district educational quality except through the organizational disruption that accompanies forecast error.

Because district performance should be unaffected in the year in which forecast errors are realized (an assumption we test directly), we estimate the impact of annual forecast errors on the achievement growth of students in the years after errors are realized. The results indicate that a 1 percentage point increase in school district forecasting error (forecasted minus actual revenues) is associated with a decline in student achievement growth of 0.003-0.004 standard deviations in the year after the error is realized—about 1-2 fewer days' worth of learning if one assumes a 180-day school year. However, the negative impact of revenue shortfalls is likely far greater in magnitude than the positive impact of unexpected windfalls.[9] Our theory is that the negative impact of shortfalls is driven by immediate organizational disruptions, as opposed to the small changes in spending levels associated with lower-than-expected revenues.[10] Indeed, as we illustrate below, the results are nearly identical whether or not we control for district spending levels. Thus, consistent with our theory, we generate

[9]For example, the school finance literature that examines the impact of tax and expenditure limits on district spending and student achievement documents significant asymmetries in the magnitude of the impacts of windfalls and shortfalls (e.g., see Downes and Figlio, 2015).

[10]We observe about a 1.5 percent decrease in spending for every 1 percent increase in a shortfall error, yet the achievement effects are those we might expect with a 10 percent change in spending (see Lafortune, Rothstein, and Schazenbach, 2016; Kogan, Lavertu, and Peskowitz, 2017).

an upper bound estimate of the impact of shortfalls on school district service delivery by estimating models in which the effects of windfalls are constrained to zero. These models indicate that when districts experience unexpected revenue shortfalls—that is, when a 1 percentage point increase in error results in actual revenues that are below the forecasted amount—student achievement growth can decline by up to 0.02 standard deviations, or about 8 days' worth of learning during the following school year.

We use a variety of tests to validate our empirical design. For example, we show that *anticipated* deviations from revenue trends had no impact on school district performance and that future realizations of forecast error are unrelated to current district performance. We also show that the negative impact of forecast error is driven by large, non-rural districts constrained in their ability to absorb shortfalls due to low fund balances. These low balances appear to be due to the Great Recession, but we found no evidence suggesting that revenue shocks associated with the Great Recession also affected student achievement through non-school factors (which would have violated the exclusion restriction). Finally, we provide evidence that revenue shortfalls indeed led to administrative disruption, including teacher attrition and efforts to raise local revenues.

The paper proceeds as follows. Section 2 provides background on school finance and district revenue uncertainty in Ohio. Section 3 describes our data; section 4 describes our empirical framework; and section 5 reviews the results. Finally, we briefly discuss this study's implications in section 6.

2 Ohio School Funding and District Revenue Uncertainty

Ohio is a typical state in many respects. It is demographically similar to the U.S.; the median school district spends just under the per pupil amount of the median U.S. school district (about $12,000 annually); and the share of revenues from federal, state, and local sources (12 percent, 44 percent, and 44 percent, respectively) matches the U.S. average (see Cornman, Keaton, and Glander, 2013).[11] Additionally, like most states across the country, its state funding system entails a combination of a minimum "foundation" for all districts and an equalization component that compensates districts with lower resident incomes and property values (Jackson, Johnson, and Persico, 2015), as the revenues districts generate at the local level come primarily from property taxes. What may make Ohio less typical, however, is the amount of uncertainty built into its funding system—particularly at the local level and during our period of study.

State funding for Ohio's 611 school districts comes primarily from the state general revenue fund, which is financed by a variety of taxes—primarily income and sales taxes, but not property taxes—and determined via Ohio's biennial budget cycle. The governor is required to present his proposed budget to the General Assembly at the start of odd-numbered calendar years, and the Assembly typically passes the final budget by the end of June (the end of the odd-numbered fiscal year). Thus, in odd-numbered calendar years, districts will be aware of a governor's proposed changes to the funding formula as early as January. On the other hand, the Assembly typically makes significant changes to that proposed formula, some of which are not made until the end of June, just before the new biennium begins.[12] Moreover, Ohio's General Assembly changed Ohio's funding formula for every biennium throughout the course of our panel[13] and state allocations to a particular district can change significantly from year to year as enrollments fluctuate—in part due to the proliferation of school choice options, such as charter schools.

Districts raise local revenues primarily by taxing real and tangible personal prop-

[11]Whether state and local shares are equal in Ohio depends on the year. For example, state share of spending recently inched above the local share, according to 2013 NCES data.

[12]For example, by May 31, 2011, districts were aware of Governor Kasich's proposed funding changes, but they were also aware of the significantly different funding plan that had passed in the House earlier in the month and the different funding plan just proposed in the Senate. They would not know until the end of June which plan—or what portions of these plans—the General Assembly would adopt for the coming and following school year (FY2012 and FY2013).

[13]All formulas entailed the distribution of funds so that there is a minimum foundation across districts, as well as extra funds for equalization purposes (e.g., to compensate districts with low taxable property wealth) and to compensate districts for the difficulty of educating certain student populations.

erty.[14] School boards governing Ohio school districts can raise local tax revenues beyond the state minimum tax floor with the approval of voters residing within the district.[15] They can also adopt a local income tax—again, with voter approval—and may raise additional funds in a variety of ways, such as fees and tuition, private donations, and investments. These sources of revenue are highly uncertain, particularly because of the frequency with which districts must consult voters to obtain them. School district tax levies often expire within five years, so districts must pursue renewal or replacement measures for those expiring levies. State law also greatly restricts the automatic growth of district revenues due to increasing property values and inflation. In particular, property tax rates above a minimum floor are adjusted as property values change so that homeowners' tax payments do not increase with increases in property values. Consequently, the vast majority of Ohio school districts operating above the minimum tax floor frequently put replacement or new measures on the ballot—measures that, on average, have just under a 51 percent passage rate (see Kogan, Lavertu, and Peskowitz, 2017)—so that revenues can keep up with rapidly increasing education costs.

The Great Recession likely contributed significantly to district uncertainty over local revenues during our period of study. Although the state requires the reduction of tax rates to offset increases in property values, it does not require an increase in tax rates in response to declines in property values. Thus, significant declines in property values associated with the Great Recession likely increased district forecasting error during the years of this study. This effect likely spread across many years and affected districts differently in any given year in part because of how Ohio property values are determined. The state requires triennial property tax updates (alternating between reappraisals and revaluations), and the timing of these updates is staggered across counties so that about one third of counties reappraise or revalue property in a given year. This fact likely contributes to the significant variation

[14] The state began to phase out the tangible personal property tax in 2009 and have been reimbursing school districts for lost revenues.

[15] Specifically, state law allows school boards, through a two-thirds vote, to place such tax measures on the ballot at four different times during most years—including November general elections, primary elections held in May, and special elections in February and August.

we observe in forecasting error between and within districts over time—making this period helpful for estimating the impact of forecasting errors on district performance.

Finally, there are also a number of federal education programs that provide revenues to districts. The largest such program is the Elementary and Secondary Education Act's Title I program, which provides funds to districts to aid in the education of economically disadvantaged students. We lack forecast data on the distribution of direct federal grant programs. However, in FY2010 and FY2011 federal stimulus funds from the American Recovery and Reinvestment Act of 2009 were distributed according to the state foundation aid formula, and the analysis includes these funds. This federal infusion of cash was used to cushion a potentially steep drop in district revenues, and some school districts in Ohio came to consider it as part of the state's unrestricted foundation aid.

It is important to note that even in years in which state formulas do not change, districts can experience significant changes in state sources of revenue due to fluctuating enrollments. These enrollment shocks can be quite significant as alternative schooling options (e.g., charter schools) are introduced or removed from year to year.[16] Additionally, local revenues are sometimes a source of significant uncertainty even when home prices are stable. Districts experience volatility in their ability to collect local property taxes, and the 211 districts with local income taxes predictably experience significant volatility in those receipts from year to year.

3 Data

3.1 District Revenue Forecasts

The Ohio Revised Code (§5705.391) and the Ohio Administrative Code (3301-92-04) require local school boards to submit "five-year forecasts" of operational revenues—as well as the

[16]That said, the relationship between revenue shocks (our instrument) and enrollment shocks is modest—between 0.06 and 0.1 depending on the analytic sample. Thus, predictably, our results are not driven by district enrollment changes. For example, controlling for enrollment shocks has no significant impact on the results (e.g., see Table A19 in the appendix).

assumptions underlying those forecasts—to the Ohio Department of Education (ODE) by October 31 of each school year and to update these forecasts between April 1 and May 31 of that same school year. The forecasts are based on fiscal years (July 1 to June 30) that roughly correspond to school years. For example, the one-year forecasts districts submitted by May 31 of 2010 are supposed to indicate what a district believes its revenues and expenditures will be for the 2010-11 school year, which corresponds to fiscal year 2011 (FY2011). The forecasts allow the state to monitor district finances and are meant to encourage districts to use a longer time horizon as they manage their finances.

District forecasts for FY2008 through FY2016 are available on the Ohio Department of Education website. Our analysis employs all of the April-May one-year forecasts (forecasts of revenues for the following school year) submitted by traditional public school districts (i.e., not charter schools). Thus, the analysis compares projected and actual revenues for FY2009 (based on forecasts made near the end of FY2008) through FY2016 (based on forecasts made near the end of FY2015). Additionally, our estimates of revenue deviations utilize three prior years of revenue data to examine deviations from that trend, as these are years that the Ohio Department of Education advises districts to consider when forecasting revenues. The forecasts include actual revenue data from FY 2005 through FY 2015 to calculate such trends.

Table 1 disaggregates local revenue data by source. As the table indicates, local sources of revenue for which there are district forecasts include the general property tax, tangible personal property tax, and municipal income tax. State revenue sources include unrestricted grants-in-aid (the basic state foundation aid we describe above), restricted grants-in-aid (additional aid for special purposes, such as transportation, educating special needs or impoverished students, vocational education, and so on), and property tax allocations (to compensate districts for tax exemptions enacted by the state).

<Insert Table 1 about here.>

Districts submit to the state separate revenue forecasts for each category listed in

Table 1. They are asked to submit their best estimates in each of these categories, along with the assumptions they used to generate them. Thus, although the state encourages districts to consider revenue trends from three prior years when generating their forecasts, districts have complete discretion in determining the estimates they submit. The one exception is that they are required to place projected revenues from upcoming levies on a separate line. These projected amounts capture the projected value of a future levy should it pass, as opposed to the expected value of the levy based on a district's beliefs about the probability of passage. Thus, besides the potential manipulation of forecasts (an issue we address below) this is the one component of the forecast data that could undermine our attempts to capture managers' expectations about revenues in an upcoming school year. However, in the analysis below, we show that the results are robust to the exclusion of district-year observations in which a forthcoming levy election is a component of a district's forecast.

3.2 Administrative Data

The analysis also employs publicly available data on school district staffing and student achievement. The data on student achievement are estimates of district "value added" as captured by growth in student scores on mathematics and reading exams. SAS Institute Inc. calculated this measure on behalf of the ODE for use in the state's accountability system. The estimates were generated by normalizing student test scores by year, subject (math or reading), and grade across the entire state, and then calculating annual student achievement gains while controlling for up to five years of prior test scores.[17] ODE reports these value-added estimates in Normal Curve Equivalent (NCE) units. We divided these estimates by

[17]Documentation of the SAS EVAAS method used to estimate value–added scores for Ohio schools is available on the Ohio Department of Education website. This online documentation indicates that, for all but the 2012-13 and 2013-14 school years, these are annual estimates of district contributions to student-level achievement gains since the previous school year. Estimates for the 2012-13 and 2013-14 school years, however, are based on a three-year composite of one-year gains in student-level test scores. We backed out the estimates of yearly student achievement gains for 2012-13 by using the one year estimates from 2010-11 and 2011-12, and then we used the 2011-12 and 2012-13 estimates to determine the one-year 2013-14 estimate. ODE confirmed that this procedure yields the one-year estimates. Finally, the publicly available estimates for 2015 and 2016 had errors, so we obtained these data directly from ODE.

21.06 (1 standard deviation on the NCE scale) to obtain the average student-level gains within a district in terms of standard deviation units.

The advantage of the value-added estimates is that they account for student educational histories and, thus, largely control for differences in district students over time.[18] The disadvantage is that they capture only limited dimensions of school district educational quality. For example, estimating school district value-added requires consecutive years of student achievement data. Because such data are only available for students in grades 3-8 (this is the range of consecutive grades in which the reading and math portions of the Ohio Achievement Assessments were administered) our analysis is limited to examining district performance in terms of educating students on testable math and reading knowledge and skills for elementary grade levels. We also know that, in part because of state and federal accountability systems, districts often protected these subject areas and grades during our period of study.[19] Thus, in this respect, our analysis might underestimate the impact of forecast error on school district performance.

But it is important to emphasize that this measure of district performance is superior to district-level measures typically used in studies that examine school and district performance. These studies typically use average proficiency rates at the school or district level—or indices of proficiency rates—to capture impacts of administrative interventions on students. One problem with this strategy is that proficiency rates are censored measures whose values are affected by changes in proficiency cut scores. Thus, they introduce significant measurement error.[20] Another problem is that average proficiency rates may simply capture changes in student composition. As we note above, the student-level achievement gains used to calcu-

[18]It would be ideal to re-estimate our models with student-level data. But the value-added measure should capture observables and unobservables, such as student motivation. Indeed, our other research during this time period has revealed that student-level data yields nearly identical estimates to analyses based on Ohio's school and district value-added estimates. Finally, as we show in Table A18 in the appendix, forecast error does not affect district enrollments or observable student characteristics.

[19]For example, Grissom, Kalogrides, and Loeb (2017) find that less effective teachers are strategically placed in untested grades and subjects.

[20]Indeed, we found that measures based on proficiency rates yield comparable effect sizes, but the estimates are imprecise and fail to attain statistical significance.

late district value-added capture district performance by accounting for student educational histories, which should be relatively robust to shifting student composition within districts. Finally, as we show below, the value-added estimates allow us to compare our effect sizes to those in the broader literature on education policy.

Although value-added estimates should be scarcely correlated with the characteristics of district students, the analysis nonetheless accounts for changes in school characteristics over time, such as student race and economic disadvantage (mostly based on eligibility for free- or reduced-price lunches), the property wealth and median income of district residents, and an index of local tax effort,[21] which is a proxy for public support for school spending and an important determinant of district revenues. Finally, we use a measure of spending per pupil in some specifications to ensure that the changes in performance we observe are not ones we would expect based purely on changes in spending levels. We obtained these data from the ODE website.

3.3 A Descriptive Look at District Characteristics and Forecast Errors

Table 2 provides some descriptive statistics based on FY2013 school district data, disaggregated according to ODE's district typology. As the table indicates, for most district types (rural, small town, suburban, and urban), districts in which residents have a higher poverty rate generally spend more per pupil (suburban schools are the exception) and have substantially lower unreserved fund balances available to absorb revenue shortfalls. Additionally, although the average district has a fund balance of around 25 percent of annual spending, the six urban districts with "very high" poverty rates have fund balances of less than 10 percent of spending.

<Insert Table 2 about here.>

[21]The index captures multiple dimensions of a district's tax burden based on both income and property wealth. A complete description of the index is available on the Ohio Department of Education website.

The table also provides the percentage error in district revenue forecasts made during the prior year—that is, forecasts made in May 2012 (FY2012) regarding revenue for the upcoming FY2013 school year. We calculated forecast error in district i and fiscal year t using the following formula.

$$Error_{it} = \frac{Forecast_{it} - Revenue_{it}}{Revenue_{it}} * 100 \quad (1)$$

As the table indicates, the average district had a forecast error of -2.03 percent for FY2013, which indicates that the typical district had a forecast that was 2 percent lower than actual revenues.[22] This margin is roughly consistent across district types, and it is consistent with what researchers have found in other contexts.[23] As Figure 1 illustrates, the overall sample reveals a similar conservative bias of -2.7. We consider this conservative bias in the analysis below.

<Insert Figure 1 about here.>

As we suggest above in our description of school finance in Ohio, there should be considerable variation in revenue uncertainty across districts and years. Indeed, as we note at the bottom of Figure 1 (and as we illustrate in Figure A1 in the appendix), the standard deviation of forecast error in any given year is remarkably consistent, ranging from a low of 3.4 percent in 2011 to a high of 4.3 percent in 2016. This variation is particularly important because the analysis controls for fixed differences in mean district performance across years.

Finally, Table 2 reports ODE's value-added estimates in standard deviation units. As one would expect given the construction of the metric, there is little variation in average value-added estimates across district types, although "very low poverty" suburban districts have an edge in terms of this metric of school district quality. Their value-added score indicates that their students experienced annual achievement gains that are approximately

[22] We removed values of forecast error that were more than 5 standard deviations from the mean.

[23] For example, Rodgers and Joyce (1996) find that the U.S. states underestimated revenues by 2.1 percent on average between 1975 and 1992. Numerous scholars have also found evidence of underforecasting at the municipal level (Kong, 2007; Bretschneider, Bunch, and Gorr, 1992).

0.05 standard deviations greater than the average student in the state. If one considers that students in grades 3-8 increase their achievement in math and reading by an average of about 0.37 standard deviations per year (see Hill et al., 2008)—and if one assumes a 180-day school year—that means that students in suburban districts with very low poverty rates experienced the equivalent of approximately 26 additional "days of learning" per year.

4 Empirical Framework

The purpose of this study is to estimate the impact of unanticipated (as opposed to anticipated) revenue shortfalls on school district performance. Our research design entails comparing changes in annual student achievement gains between districts that experienced differential changes in forecasting error. We also use an instrumental variables approach in order to isolate the impact of true errors in districts' beliefs about future revenues, as districts have incentives to manipulate their official revenue forecasts. In this section, we further describe our research design and the two-stage-least squares (2SLS) models we use to implement it.

A central challenge in quantifying school districts' beliefs about future revenues is that the revenue forecasts they publicize may not truly reflect those beliefs. For example, as Table 2 indicates, revenue projections in our dataset have a conservative bias, which is consistent with districts adjusting revenue forecasts downward, perhaps due to risk aversion or to convince voters, state policymakers, or potential donors that they need more funds. On the other hand, districts also have incentives to inflate their forecasts if they want to make it look as if they are in good financial health (e.g., to avoid state intervention).[24] Moreover, forecast manipulation and school district performance could be correlated. For example, districts may be more inclined to understate their revenue forecasts in years in which they are distracted from their educational function because they are busy lobbying policymakers

[24] See Thompson (2016) for an analysis of the consequences of state interventions in the finances of Ohio school districts.

or marketing tax increases to voters, which could lead to lower district performance. And, of course, a district's managerial competence may affect both forecast accuracy and student learning.

To address these problems, we use deviations from a district's revenue trend as a plausibility exogenous source of forecasting error to identify the causal impact of faulty beliefs about revenues on district performance. Specifically, we estimated the following two-stage-least-squares (2SLS) model, where the error in school districts' official revenue forecasts is the endogenous variable of interest.

$$Error_{i,t-1} = \pi_1 RevDev_{i,t-1} + \pi_2 RevDev_{i,t-2} + C_{it}\Pi + \gamma_i + \zeta_t + \upsilon_{it} \tag{2}$$

$$Error_{i,t-2} = \theta_1 RevDev_{i,t-1} + \theta_2 RevDev_{i,t-2} + C_{it}\Theta + \omega_i + \kappa_t + \eta_{it} \tag{3}$$

$$VA_{it} = \delta_1 \widehat{Error}_{i,t-1} + \delta_2 \widehat{Error}_{i,t-2} + C_{it}\Phi + \rho_i + \lambda_t + \epsilon_{it} \tag{4}$$

The first endogenous variable ($Error_{i,t-1}$) is the percent difference between district revenues at time $t-1$ and the revenues the district had projected one year prior ($t-2$). The second endogenous variable ($Error_{i,t-2}$) is the percent difference between district revenues at time $t-2$ and the revenues the district had projected one year prior ($t-3$). The two instruments ($RevDev_{i,t-1}$ and $RevDev_{i,t-2}$) capture differences between district-specific revenue trends and actual revenues at the time the errors were realized. (We detail the construction of these variables in the next section.) The vector C_{it} includes a number of time-varying control variables, including district per-pupil spending; the parameters ρ_i, ω_i, and γ_i capture district fixed-effects; and ζ_t, κ_t, and λ_t capture year fixed-effects.[25]

The predicted values of the forecast errors estimated in equations 2 and 3 ($\widehat{Error}_{i,t-1}$ and $\widehat{Error}_{i,t-2}$) enable us to estimate the parameters of primary interest (δ_1 and δ_2). The parameter δ_1 captures our estimate of the impact of a one-year revenue forecast error realized

[25]The raw data have a few outliers that appear to be due to errors in data entry. We handled this by winsorizing outliers more than 5 standard deviations from the mean. The results are similar without this correction.

one year prior $(t-1)$ on annual district value-added performance, VA, in district i at time t. In other words, δ_1 should capture the impact of revenue truly diverging from district expectations. (Ultimately, in the analysis below, we seek to isolate the impact of less-than-expected revenue—that is, the impact of unanticipated revenue shortfalls.)

We focus on the lag of a one-year forecast error because districts should be unable to react to forecast error until the school year after a revenue shortfall or windfall occurs. Recall that a one-year forecast error is an error in a May forecast of revenues for the upcoming school year. Districts may discover if revenues are falling short of expectations as the upcoming school year progresses, but they are unlikely to fully appreciate the implications or be able to react until the school year is over (an assumption we test below). Indeed, the "forecasts" of current-year revenues and expenditures districts submit during the April/May window reveal substantial error, and it is not until the following school year that actual revenues and expenditures are reported. Moreover, because districts are heavily constrained in their ability to allocate resources (e.g., due to restrictive labor contracts), it may be two years after a shortfall or windfall occurs that a district can fully react. Thus, we also estimate the parameter δ_2, which captures the impact of a one-year forecast error that occurred two years prior $(t-2)$.

4.1 Using Deviations from Revenue Trends as an Exogenous Source of Variation

The above model assumes that revenue deviations from district-specific trends provide an exogenous source of variation in one-year revenue forecast errors. We estimated these deviations for each district-year observation using the following OLS model.

$$Y_t = \alpha + \beta_1 \cdot \mathbf{1}[Year_t = T] + \beta_2 Year_t + \epsilon_t \tag{5}$$

Y is district revenue at time t and Year is the fiscal year. Each district-specific model is estimated using data from the current fiscal year ($Year_t = T$) as well as revenues from three prior fiscal years, as those are the years the state encourages districts to consider. Thus, β_2 is the estimated linear trend in revenues and β_1 is the deviation from that trend in fiscal year T. We then divided the estimated deviation by the revenue in the previous fiscal year to capture the percent deviation in revenues ($RevDev$ in equations 2 and 3 above).[26] Finally, we multiplied by -1 so that positive values indicate unanticipated shortfalls.

This instrument is a strong predictor of forecast error, as we illustrate below. We also believe that it should meet the other assumptions of the instrumental variables design. First, the independence assumption stipulates that, conditional on covariates, an instrument must be as good as randomly assigned. It seems reasonable to assume that, conditional on district and year fixed effects, revenue deviations from a three-year trend are essentially random and, thus, uncorrelated with unmeasured causes of districts' annual value-added. As a sensitivity analysis we also include a rich set of time-varying controls for well-established determinants of student achievement, including per-pupil spending, student poverty rates, and residential incomes. And the district value-added measure of achievement growth is based on student-level analyses that account for multiple prior years of student achievement, which research has shown accounts quite well for omitted student-level variables when estimating school and teacher quality (e.g., see Deming 2014; Chetty, Friedman, and Rockoff, 2014b). Finally, our instrumenting for a second lag of forecast error should account for residual effects of prior revenue shocks. For example, a district that experiences a significant forecast error due to a revenue shock might approach forecasting differently in a subsequent year, and districts that experience consecutive revenue shocks may respond differently to the second shock because of their experience with the first.[27]

[26] The results of the analysis are similar if we scale the deviation using the current fiscal year. We provide these results in the appendix.

[27] As the results indicate, including a second lag—the preferred specification in equation 5 above—strengthens and increases the precision of our estimates. Including a third lag reduces precision significantly, which is why we present models with no more than two lags.

Second, the exclusion restriction stipulates that the impact of an instrument should be solely through the endogenous variable of interest. Conditional on district fixed effects and well established predictors of student learning and district quality, we argue that deviations from revenue trends should not directly affect district performance other than through revenue uncertainty as captured by forecast error. There are a couple of readily apparent ways in which the exclusion restriction might be violated. First, revenue shocks might affect achievement through school-based factors that are unaffected by forecast error. In particular, revenue shocks correlate with changes in per-pupil spending and, thus, may affect student learning through both unanticipated revenue deviations (i.e., forecast error) and anticipated revenue deviations. However, as we show in some validity checks below, there is no significant relationship between *anticipated* revenue deviations and student achievement, and the results are the same whether or not we control for spending per pupil. That is consistent with research indicating that the achievement effects of increased spending can take some time to accumulate.[28] Additionally, as we show below, the negative impact of shortfalls is significantly larger than the positive impact of windfalls. That corroborates our theory that the impact of forecast error occurs primarily through organizational disruption, as opposed to changes in spending levels associated with lower-than-expected revenues. Thus, there are theoretical and empirical reasons to believe that the school-based factor through which revenue deviations affect student achievement is solely the error in district revenue forecasts.

Violation of the exclusion restriction could also occur if revenue shocks were correlated with non-school determinants of student learning. In particular, the Great Recession affected school district revenues, but it also likely affected students' general well being. For example, if students experienced stress because of unemployment in their household, that could affect their learning (e.g., see Dahl and Lochner, 2012: Ananat et al., 2013). We explored this possibility by comparing the impact of forecast error between districts that

[28] Additionally, we observe about a 1.5 percent decrease in spending for every 1 percent increase in a shortfall error, yet the immediate achievement effects are those we might expect with a 10 percent change in spending (see Lafortune, Rothstein, and Schazenbach, 2016; Kogan, Lavertu, and Peskowitz, 2017). Thus, we should not expect the funding changes we observe to have an immediate effect.

were more and less severely hit by the recession, as measured by changes in unemployment rates between 2007 and 2009.[29] We also estimated models restricted to years after the Great Recession and the effect sizes actually strengthen a bit. Thus, as we show below, both sets of analyses suggest that the impact of forecast error on school district value-added is not the result of the Great Recession's immediate impact on non-school determinants of student achievement.

Finally, one might worry that deviations from three-year revenue trends that districts do anticipate are correlated with errors in official district forecasts. If that were the case, then we would be unable to completely isolate true errors in district beliefs. This would be a problem if, for example, districts simultaneously anticipated revenue shocks and biased publicized forecasts in ways that feigned ignorance of those shocks. This would likely put a downward bias on our estimated impact of shortfalls, for example, as districts would be able to plan for these shocks and minimize disruption. We believe it is unlikely that this leads to a systematic bias in our analysis—particularly because we include district and year fixed-effects, as well as a set of time-varying covariates, including a second lag of forecast error.[30] While we are unable to definitively rule out this possibility, at the very least our instrumental variables approach should lessen the downward bias from reduced-form models that assume revenue deviations from trends are themselves good measures of districts' revenue uncertainty.

[29] Like Yagan (2017), we find that the percentage point difference between 2009 and 2007 county unemployment rates is scarcely related to pre-recession unemployment trends.

[30] One reason our main analysis could potentially violate this assumption is that the revenue forecasts we use include projected revenues for levy elections scheduled for the upcoming school year. As we note above, projected levy revenues are those a district would receive if a levy were to pass—they are not adjusted for district beliefs regarding the probability of passage. This could result in a correlation between anticipated revenue shocks and forecast error. For example, if a district were relatively certain that a scheduled replacement levy will fail during the upcoming school year, it would both anticipate the revenue deviation from a three-year trend and it would incorporate the full levy amount into its forecast, leading to a large measured error. That said, as we note above, levy passage rates hover at around 51 percent, so they amount to a coin flip in most districts. Consequently, such a link between anticipated revenue deviations and forecast error should simply lead to measurement error, as opposed to bias. Indeed, supplementary analyses that we present below reveal that the results are even stronger if we exclude district-year observations that include forecasted revenues from upcoming levy referenda.

5 Results

We begin by providing some descriptive statistics of key variables (Table 3) and the first stage results (Table 4). Our preferred model, captured by equation 4, includes two lags of forecast error. However, we also estimated models using one lag (including one endogenous variable and one instrument). Table 4 presents the first stage results for both of these specifications. As the table reveals, instrumenting for two years of forecasting error enhances significantly our ability to predict one-year forecast error realized at time $t-1$. The Angrist-Pischke F-tests for the excluded instruments yield F-statistics of 96.8 and 128.7 for $RevDev_{i,t-1}$ and $RevDev_{i,t-2}$, respectively. Nevertheless, in the results below we sometimes provide the results of models with one lag of forecast error for comparison.

<Insert Tables 3 and 4 about here.>

The remainder of this section proceeds as follows. First, we provide the results of OLS and 2SLS models with and without covariates, such as per-pupil spending. We also report the results of these models using alternative measures of student achievement, forecast error, and revenue shocks. Second, we provide the results of placebo tests to examine the validity of our primary model described by equation 4 above. Third, we alter this model to focus on the impact of unanticipated shortfalls. Fourth, we explore possible mechanisms and effect heterogeneity to further examine the validity of our empirical strategy.

5.1 Impact of Forecasting Error on School District Value-Added

Tables 5 and 6 present estimates of the impact of district forecasting error on the annual achievement growth of district students. In each table, we begin by presenting the results of OLS models that include the endogenous forecast error variables as if they were exogenous predictors of school district value-added. These models suggest that increasing forecast error by one percentage point has a negligible effect on student achievement growth one or two years after the error is realized, and the coefficients do not approach conventional levels of statistical significance. The reduced-form models reported in columns 3 and 4 yield small coefficients but, importantly, the second lag of revenue volatility yields a statistically significant impact of almost -0.001 district-level standard deviations.[31] These results suggest that the realization of lower revenue, as compared to that predicted by a three-year linear revenue trend, has a negative impact on student achievement growth in math and reading two years later. Notably, the estimates are strikingly similar whether we include time-varying district controls (Table 6) or exclude them (Table 5).[32]

<Insert Tables 5 and 6 about here.>

The 2SLS estimates in the final two columns of Table 5 and Table 6 isolate the impact of shock-induced errors in official district forecasts. In particular, the results in column 6 of both tables indicate that a 1 percentage point increase in forecast error is associated with statistically significant declines in district value-added of almost 0.004 standard deviations in annual student achievement growth the following school year, and a decline of around 0.002 two years later. Assuming a 180-day school year and average annual achievement growth in math and reading of around 0.37 standard deviations across grades 3-8 (see Hill et al, 2008), that corresponds to about two fewer "days of learning" for every district student.

Table 7 disaggregates these effects by grade level. As the results in the table reveal, the negative impact of forecasting error is more pronounced in grades 4 and 5 than in later grades. It is worth keeping in mind that students have greater average learning gains in earlier grades, with an average of 0.46 for grades 4 and 5 (Hill et al, 2008). Thus, except for grade 6, these results equate to about two days of learning for each grade level. Nonetheless, the two days of learning losses are more significant for earlier grades because students in early grades tend to learn more from year to year.

We re-estimated these models with a number of alternative performance measures.

[31] In the context of 2SLS, the "reduced form" model comes from including the instrument directly into the structural equation, which yields the "reduced-form effect" of the instrument (e.g., see Angrist 2006).

[32] As Table A1 in the appendix indicates, the results are also robust to including or omitting spending per pupil, whether or not we include the other covariates.

First, we re-estimated the models using a normalized version of Ohio's "performance index," which is based on counts of students at various proficiency levels. The coefficient estimates are comparable to those we present above, but the results do not attain statistical significance (see Table A2 in the appendix). As we argue above, this is to be expected, as this proficiency-based metric contains significant measurement error. Second, we re-estimated the models using a value-added estimate for math only (see Table A3 in the appendix). We did so to address concerns regarding ODE's 2016 value-added estimates in reading, which are negatively correlated with 2015 value-added estimates and uncorrelated with 2012-2014 value-added estimates.[33] The results are qualitatively similar if we focus on achievement gains in mathematics.

We also re-estimated these models using slightly different constructions of the instrument. First, we re-estimated the models using a measure of revenue deviations scaled by current revenues, as opposed to the previous year's revenues. The results are nearly identical (see Tables A4-A6 in the appendix). Second, we estimated models using an instrument based on deviations from four prior years of revenue, as opposed to three. There is a similar pattern of results for the main results (see Tables A7-A9 in the appendix).[34] However, the coefficient estimates are smaller in magnitude. It might be that the inclusion of one more prior year of revenue—one more year than the state recommends as a minimum—makes this instrument a stronger predictor of forecast error among relatively sophisticated districts. If that is the case, the LATE we estimate with our primary instrument places greater weight on the forecasts of relatively unsophisticated districts that use less information when generating their forecasts. Whatever the particular cause, these more modest effect sizes support the notion that the results of our main models may capture an upper bound.

Finally, we estimated models that omit observations for which forecast error was measured based in part on future levy revenues, as projected levy revenues are accounted

[33]It appears that the transition to new academic content standards may be responsible for these odd estimates of district effectiveness. Fortunately, the estimates in math are correlated with estimates from prior years and, thus, allow us to check that our findings are not an artifact of the change in standards.

[34]The results are also similar across the various validity checks we perform below.

for in a way that does not capture a district's beliefs about the probability that a levy will pass. The estimated impact of forecast error increases in magnitude when we remove these observations from the sample (see Table A10 in the appendix).

Overall, the results indicate the potential importance of our modeling approach. First, the estimated effects based on our 2SLS model are about four times greater than those we get from a reduced-form model that assumes deviations from trend capture school district uncertainty. That is understandable, as districts often consider far more than three years of prior revenues when generating their forecasts. Indeed, the documentation districts submit with their forecasts indicates that they are often quite sophisticated as they attempt to predict future enrollments, tax receipts, and changes to the state's funding formula, for example. Such sophistication should significantly attenuate the estimated effect when analyses use deviations from trends as measures of uncertainty. Second, the results indicate that naive regressions that assume official forecasts capture districts' true beliefs about future revenues may not come close to generating accurate estimates of the impact of forecast error on educational outcomes. The results are consistent with anecdotal evidence that districts manipulate their official forecasts significantly. For example, if districts understate revenues when they wish to argue for new taxes or changes to funding formulas, they may simultaneously improve district value-added and increase errors in official forecasts. Similarly, if districts switch between strategies of understating revenues and overstating revenues (e.g., in years in which they are concerned about political interventions), that could introduce sufficient noise to wipe out the estimated effects of forecast error.

5.2 Placebo Tests

We conducted placebo tests to support the causal interpretation of these findings. First, we checked whether forecast errors to which districts should be unable to respond—those that are realized in the fiscal year (t) during which student learning is measured or those occurring in the future (fiscal year $t+1$)—had an effect. If such an effect were present, it would suggest that some unmeasured factor correlates with both forecast error and student achievement growth. As Table 8 indicates, however, we detect no statistically significant effects and our initial estimates for the lagged values of forecast error remain similar, whether (column 1) or not (column 2) we include covariates.

<Insert Table 8 about here.>

Second, we checked whether anticipated revenue deviations had an impact on student achievement growth. Recall that our theory stipulates that such deviations should have no impact on district performance, as districts that anticipate the relatively minor revenue shocks at hand should be able to absorb them without affecting student achievement measurably. If anticipated revenue shocks had an impact on performance, however, then the exclusion restriction would fail to hold in our primary 2SLS models as this factor would serve as a direct link between deviations from revenue trends and student achievement. To check this possibility, we estimated the following 2SLS model.

$$RevDev_{i,t-1} = \pi_1 ForRevDev_{i,t-1} + \pi_2 ForRevDev_{i,t-2} + C_{it}\Pi + \gamma_i + \zeta_t + \upsilon_{it} \tag{6}$$

$$RevDev_{i,t-2} = \theta_1 ForRevDev_{i,t-1} + \theta_2 ForRevDev_{i,t-2} + C_{it}\Theta + \omega_i + \kappa_t + \eta_{it} \tag{7}$$

$$VA_{it} = \delta_1 \widehat{RevDev}_{i,t-1} + \delta_2 \widehat{RevDev}_{i,t-2} + C_{it}\Phi + \rho_i + \lambda_t + \epsilon_{it} \tag{8}$$

The endogenous variables are revenue deviations at time $t-1$ and $t-2$. The two instruments ($ForRevDev_{i,t-1}$ and $ForRevDev_{i,t-2}$) capture the difference between *forecasted* revenues and realized district-specific revenue trends. The vector C_{it} includes a number of time-varying control variables, but not per-pupil spending; the parameters ρ_i, ω_i, and γ_i capture district fixed-effects; and ζ_t, κ_t, and λ_t capture year fixed-effects. Thus, δ_1 should capture the impact of anticipated revenue changes on student achievement growth.

As the results in Table 9 indicate, however, we find no such effect. Revenue deviations that districts anticipated do not correlate with student achievement growth. Although the exclusion restriction is ultimately untestable—there is no way of definitively ruling out alternative paths—these results at least provide some validation of our approach.

<Insert Table 9 about here.>

5.3 Impact of Revenue Shortfalls

The estimates above assume that the impact of forecast error is the same whether a district is experiencing a windfall or shortfall—that is, whether actual revenues are above or below forecasted revenues. As we note above, however, the negative impact of revenue shortfalls is likely far greater in magnitude than the positive impact of unexpected windfalls (e.g., see Downes and Figlio, 2015). Indeed, our theory suggests that windfalls should have no effect on district performance because the negative impact of shortfalls is driven by immediate organizational disruptions, as opposed to the small changes in spending levels associated with forecast errors.[35] Thus, consistent with our theory, we generated an upper bound estimate of the impact of shortfalls on school district service delivery by estimating models in which the effects of windfalls are constrained to zero.[36] These results are presented in Table 10.

<Insert Table 10 about here.>

The results indicate that, on average, a shortfall leads to a decline in value-added of 0.05 standard deviations relative to windfalls (columns 1-2). Columns 3-4 indicate that, assuming there are no positive effects tied to windfalls, a one percentage point increase in error involving revenue shortfalls leads to a decline in student achievement growth of 0.022 standard deviations during the following school year (the equivalent of about 8 days

[35]We observe about a 1.5 percent decrease in spending for every 1 percent increase in a shortfall error, yet the achievement effects are those we might expect with a 10 percent change in spending (see Lafortune, Rothstein, and Schazenbach, 2016; Kogan, Lavertu, and Peskowitz, 2017). We also know that increases in spending levels can take years to take effect (Lafortune, Rothstein, and Schazenbach, 2016) and, as we illustrate above, the results are nearly identical whether or not we control for district spending levels.

[36]We also attempted to model the non-linear effects of forecast error by using interactions of revenue deviations from trends as instruments for the interacted endogenous variables. Unfortunately, we had insufficient statistical power for this analysis. Nevertheless, we believe our analysis of upper and lower bounds to be sufficiently informative.

of learning), and the negative effect is about half as large two years later. Once again, it is important to note that including covariates—such as per pupil expenditures—does not meaningfully affect the results. The shortfall effects are also nearly identical whether we take account of the conservative bias of district forecasts by defining a shortfall as forecast errors above -2.7.

5.4 Possible Mechanisms and Effect Heterogeneity

The results are the same whether or not we control for per-pupil spending, so the impact of forecast error is unlikely to be attributable to any link between achievement growth and district spending levels.[37] Thus, in this section we examine the alternative mechanisms stipulated by our disruption theory as well as effect heterogeneity. Importantly, these heterogeneity analyses enable us to explore how the Great Recession factors into our results and provide further checks on the validity of our IV design.

First, we consider the impact of forecast error on teacher attrition as captured by the percent of district teachers observed at time $t-1$ who were no longer in the district at time t. Table 11 reveals that a one percentage point increase in forecast error increases the observed teacher attrition rate by around 0.2 percentage points the following year, and about half of that two years later. Consistent with the student achievement models, the magnitude of this effect increases by a factor of over 4 when we estimate the impact of forecast errors associated with shortfalls (see Table A11 in the appendix). These results correspond to a decline in teacher counts and an increase in student-teacher ratios (see Table A12 in the appendix). Moreover, an analysis of spending impacts indicates that districts experiencing shortfalls implemented spending cuts of around 1.5 percent for every 1 percent increase in forecast error (see Table A13 in the appendix). These additional results are consistent with the story that teacher attrition was spurred by disruptions surrounding proposed or realized spending cuts.

[37] See Table A1 in the appendix for results when only spending is removed.

<Insert Table 11 about here.>

Table 11 also indicates that the probability that a district places a new tax levy on the ballot increases by 0.01—or about 1 percentage point—the following year for every 1 percentage point increase in forecast error. This effect increases in magnitude by a factor of around 2 if the analysis is limited to forecast errors involving shortfalls (see Table A11 in the appendix). On the other hand, as one would expect, forecast error does not affect the probability that a replacement levy is placed on the ballot. The timing of replacement levy elections is generally set, resulting from the expiration of a prior levy. Thus, the analysis of replacement levies serves as a sort of placebo test for this mechanism.

One should also expect that errors are more consequential if districts have low fund balances. Across all years of the panel, the median district has an average fund balance of 22.2 percent of revenues. Table 12 indicates that the negative achievement impacts we present above are driven by districts that have fund balances below 22 percent of total revenues. This difference in effects between districts with high and low fund balances is significant at the 0.01 level.[38] The table also indicates that the negative achievement effects are concentrated in districts with enrollments above the median of 1,732 students (p=0.054).[39] Because only urban and suburban districts have average enrollments above this median level, this result raises the question of whether forecast error is an urban problem. Table 13 reveals that our results are driven entirely by districts in urban areas (cities and towns, but not rural areas). This difference is statistically significant (p=0.018).

<Insert Table 12 and Table 13 about here.>

[38]We examined this important mechanism further by splitting the sample based on fund balances in 2008 and found similar results (see Table A14 in the appendix). We also examined the results when we split the sample into thirds. The estimates are noisy but the relationship between fund balance and the impact of forecast error is essentially linear (see Table A15 in the appendix). The coefficient is -0.002 for the top third, -0.004 for the middle third, and -0.006 for the bottom third.

[39]The difference in impact is negligible (both substantively and statistically) between districts that ODE labels as “high poverty” and “very high poverty”, as opposed to those labeled with “low” or “average” levels of poverty.

At first glance, it appears problematic that large, non-rural districts are disproportionately affected, as larger districts should be better able to absorb revenue shocks. The explanation is straightforward, however: large, non-rural districts were those with low fund balances as a percent of revenues. The median fund balance for high-enrollment districts was 19.6 percent, but it was 25 percent for low-enrollment districts. If we focus on initial fund balances from 2008, the median for large districts was just 16.9 percent of revenues, whereas it was 25 percent of revenues for small districts. These differences are statistically significant and should go a long way toward explaining the effects we detect among high-enrollment districts. On the other hand, as Table 13 indicates, the amount of charter school competition districts faced in 2008 seems to be unrelated to the impact of forecast error on school performance.[40]

Thus, it appears that fund balances played an important role. But why might a one percentage point increase have such a large impact among districts with average fund balances below 22 percent? The median fund balance of 11.9 percent among these districts might appear sufficient to absorb such shocks. However, many Ohio districts have rules or guidelines for reserve balances. Keeping a certain amount in reserves can be important for a variety of reasons, including maintaining credit ratings. A recent report indicates that, among districts surveyed, internal rules or guidelines for fund balances or reserves ranged between 0 and 180 days of operating revenues, with 90 days being most commonly mentioned (Patton, 2015). Assuming a nine-month school year, that is about 33 percent of annual operating revenues. But it was not until 2016 that the median district had a fund balance near that level (up from under 20 percent in 2008). It appears that districts may have sought to increase those reserves over the years of our panel (e.g., by cutting costs and placing levies on the ballot), perhaps especially if they experienced shortfalls during some of those years.

Finally, it is worth considering the impact of the Great Recession. First, it could be

[40]Districts that face significant charter school competition are disproportionately urban and nearly all are poor performers according to the state's performance index. One might imagine that districts facing such competition are under greater fiscal pressure and that their performance might decline simply because their relatively motivated students were more likely to pursue choice options.

that the recession is responsible for the low initial fund balances we discuss above. Indeed, the median fund balance was 19 percent of revenues in 2008. It then rose to 22.3 percent of revenues in 2010 and, eventually, 31 percent of revenues in 2016. This evidence is consistent with the notion that the recession significantly depleted fund balances and that districts spent subsequent years trying to build them back up. However, it might also be that recession-related revenue shocks affected student achievement through non-school factors, which would be a violation of the exclusion restriction. For example, as we note above, unemployment could lead to household stress that affects students' learning (e.g., see Dahl and Lochner, 2012: Ananat et al., 2013). To check for this, we first re-estimated the models using only non-recession years (dropping the first two years of our sample). The estimated effects increase somewhat in magnitude when we drop those years (see Table A16 in the appendix). Second, we split the sample based on the recession's intensity, as measured by the percentage point change in county unemployment rates from 2007 to 2009. The impact of forecast error is driven by districts that were relatively unaffected by the Great Recession (see Table A17 in the appendix). Overall, these results suggest that the Great Recession constrained districts' abilities to absorb lower-than-expected revenues, but we find no evidence that the results we present are due to the recession's impact on non-school determinants of student learning.

6 Discussion

To our knowledge, this analysis is the first to estimate the impact of year-to-year revenue uncertainty on the performance of local governments. Revenue uncertainty has become a highly salient issue, as state revenues are increasingly volatile and difficult to predict (PEW, 2015), and as Congress's inability to enact budgets has led it to rely on last-minute and short-term spending bills to maintain government operations. There is a general sense—and a lot of anecdotal evidence—that such revenue uncertainty has a significant negative impact on the performance of agencies that manage public programs, but those impacts are difficult to quantify. Leveraging a measure of revenue forecasting error that captures a wide variety of funding sources—and using an organizational performance metric that allows us to draw valid comparisons across hundreds of similar public agencies—this study makes significant progress in documenting the impact of revenue uncertainty.

Specifically, the analysis indicates that errors in revenue forecasts had a significant effect on the educational delivery of school districts in Ohio. These results are driven by school districts that were below the state median in terms of their cash balances (as a percent of revenues) and that have high enrollments, which magnifies the substantive significance of the effects we find. The analysis also reveals that forecasting error leads to teacher attrition and district efforts to raise funds via new tax levies. Overall, the results indicate how significant the negative impact of forecasting errors can be. The administrative disruptions to which they contribute seem to have an out-sized impact, beyond the impact one would expect due to associated changes in revenue levels.

One limitation of our analysis is that the results appear to be somewhat sensitive to modeling choices. For instance, when we use four-year revenue trends rather than three, our estimates decrease somewhat, perhaps indicating that our main results are driven by districts that are less sophisticated in their forecasting. Additionally, the low fund balances that districts had due to the Great Recession seem to have further constrained their ability to absorb revenue shortfalls during the years under study. These points do not undermine the validity of our empirical design, but they do suggest that the estimates we generate could be on the high end of the distribution.

These results have a number of potential policy implications. For example, research indicates that the centralization of school funding has led to more equitable and, in some cases, higher per-pupil spending levels across districts (Cascio and Reber, 2013; Jackson, Johnson, and Persico, 2015; Hill and Kiewiet, 2015), as well as increased student achievement (Jackson, Johnson, and Persico, 2015; Lafortune et al., 2016). But there may be costs to such centralization. For example, restrictions in how districts can use state and federal funds can prevent administrators from allocating funds toward their most productive uses (Roza, 2013), which might limit their ability to absorb revenue shocks. Additionally, some contend that centralization has introduced greater uncertainty in district finances by shifting funding from a relatively stable property tax base to relatively volatile income and sales tax bases, and by introducing state and federal budgetary politics into the mix (Ványolós, 2005).

The results are also consistent with the notion that maintaining higher fund balances could protect school districts from the adverse consequences of forecast errors. Roughly, our analysis indicates that districts with average fund balances lower than 22 percent of annual revenues (11.9 percent, on average) were unable to absorb revenue shocks without experiencing a decline in performance. It is important to keep in mind that our period of analysis includes the Great Recession. Thus, this may be on the high end of what districts need in regular times. It also is important to keep in mind that district managers may not have the discretion to maintain larger balances, even if they prefer it. As we note above, district residents may be less likely to approve tax levies, and state policymakers sometimes threaten to reduce funding to districts that they perceive to be hoarding cash. Nevertheless, this study suggests that the minimum fund balances that some Ohio districts keep may be too low to stave off the negative performance effects we detect.

More generally, we hope to see a growing body of research examining the impact of revenue uncertainty on service delivery. Public administrators have long lamented the difficulties of strategic planning when revenue streams are uncertain. For example, it is common for them to complain about how late in the fiscal year state budgets are adopted. Yet, anecdotal evidence suggests that the timing of public budgeting is getting worse. Indeed, political conflict seems to introduce significant delay in state and federal budgeting processes. It may be that the inefficiencies that last-minute budgets introduce are not as well appreciated as the spending levels over which policymakers debate. This study reveals that the costs in terms of the performance of public programs can be substantial.

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Table 1. Sources of Local and State Funding Across Ohio Districts

Funding Source	Description	Average (millions)	Percent of Total
Local			
General Property Taxes	Taxes on assessed valuation of real property located within the school district.	11.9	43.4
Tangible Personal Prop. Taxes	Taxes on equipment or supplies/materials of businesses that reside within the school district.	0.51	1.9
Income Taxes	Taxes on those who file Ohio individual income tax returns within the district.	0.59	2.2
Total Local	*Sum of local revenues*	13.0	47.4
State			
Unrestricted Grants-in-Aid	Funds districts receive through Ohio's foundation program on which the state does not impose spending restrictions.	10.5	38.3
Restricted Grants-in-Aid	Funds districts receive through Ohio's foundation program that are restricted for specific purposes (e.g., career and technical education).	0.04	0.1
Property Tax Allocation	Transfers to cover district revenue losses associated with various state programs, such as the rollback of the tangible property tax and business property tax exemptions.	2.26	8.2
Total State	*Sum of sources of state funding*	12.8	46.7
Total (State & Local)	The total of the above revenue sources, as well as other miscellaneous local and state revenues. For the FY2010 and FY2011 school years, this includes federal stimulus funds distributed according to Ohio's foundation aid formula.	27.4	100.00

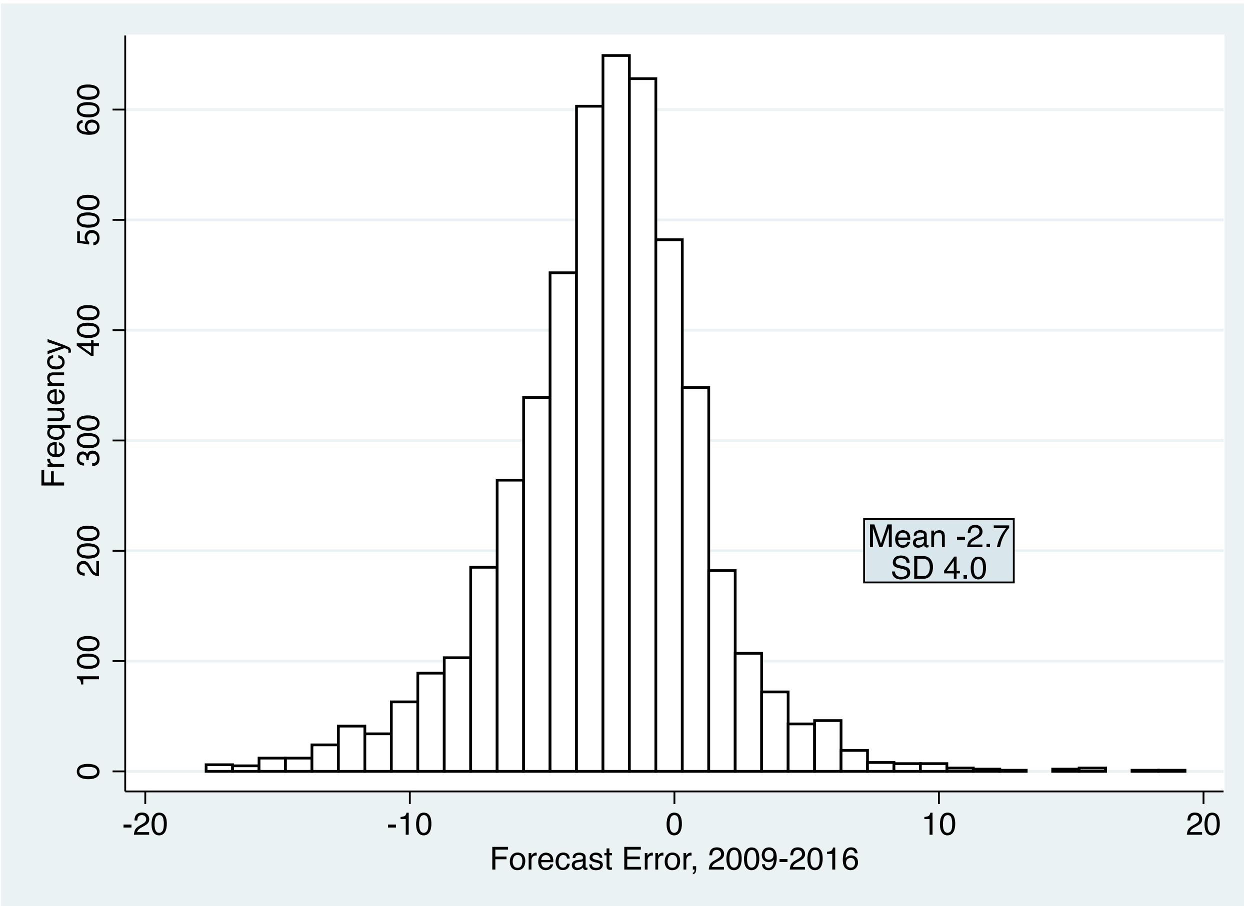
Note: The breakdowns are based on actual revenues across 608 of Ohio's 611 districts during fiscal year 2013.

Table 2. District Characteristics, Forecast Error, and Value Added (FY2013)

District Typology	District Count	Enroll-ment	Percent Disad-vantaged	Spending Per Pupil	Fund Balance Per Pupil	Forecast Error	Annual Value-Added
Rural							
High Poverty	123	1,327	50.1	$9,410	$2,310	-2.46	0.000
		(700)	(12.9)	(1,112)	(1,893)	(4.22)	(0.070)
Average Poverty	107	998	40.0	$9,346	$3,039	-2.08	0.006
		(400)	(15.5)	(908)	(2,317)	(3.26)	(0.067)
Small Town							
Low Poverty	111	1,632	32.6	$9,003	$2,139	-2.10	0.015
		(734)	(10.4)	(1,265)	(1,833)	(3.07)	(0.059)
High Poverty	89	2,161	55.1	$9,403	$1,910	-1.11	0.013
		(976)	(13.4)	(1,084)	(1,807)	(3.22)	(0.059)
Suburban							
Low Poverty	77	4,097	29.6	$10,364	$2,351	-2.36	0.029
		(2,015)	(12.8)	(2,180)	(2,077)	(2.77)	(0.046)
Very Low Poverty	46	5,201	13.1	$11,886	$3,699	-1.78	0.054
		(4,260)	(8.33)	(2,705)	(3,258)	(3.52)	(0.043)
Urban							
High Poverty	49	4,455	68.5	$11,222	$1,990	-1.99	0.004
		(3,180)	(16.8)	(2,060)	(1,847)	(3.64)	(0.051)
Very High Poverty	6	29,192	87.0	$13,678	$1,154	-2.68	0.007
		(13,096)	(12.5)	(860)	(661)	(2.44)	(0.037)
All Districts	608	2,617	42.3	$9,820	$2,421	-2.03	0.01
		(3,671)	(19.6)	(1,794)	(2,149)	(3.44)	(0.06)

Note. The table provides means and standard deviations (in parentheses) for key district-level variables. The value-added number for 2013 is adjusted from the three year average (see note in text).

Figure 1: Distribution of Forecast Error



Note: The histogram presents the number of districts with forecast errors of a particular size. The sample covers all years of forecast error data included in the analysis below. The mean and standard deviation (respectively) of forecast error by year are as follows: 2009 (-0.7, 3.7), 2010(-1.2, 4.2), 2011(-2.2, 3.4), 2012(-2.6, 3.8), 2013(-2.0, 3.4), 2014(-4.5, 3.5), 2015(-3.3, 3.6), 2016(-4.8,4.3).

Table 3. Summary Statistics for Regression Variables

	(1) Mean	(2) SD	(3) Min	(4) Max
Forecast Error	-2.7	4.0	-25.9	20.4
Deviation from Trend	-0.5	5.7	-34.1	33.0
Percent Economically Disadvantaged	40.6	20.2	0.0	100.0
Log Median Income	10.4	0.2	9.7	11.2
Tax Effort	1.0	0.3	0.2	3.3
Percent Non White	13.1	17.7	0.0	100.0
Percent Limited English Proficiency	1.1	2.8	0.0	54.8
Log Spending Per Pupil	9.2	0.2	7.4	10.0
Fund Balance as Perc of Revenues	25.5	18.5	-13.5	142.1
District Value-Added	0.0	0.1	-0.4	0.4
Teacher Attrition Percentage	10.2	5.0	0.0	58.8
New Levy	0.04	0.2	0.0	1.0
Replacement Levy	0.04	0.2	0.0	1.0
Enrollment	2,644	3,784	228	51,963
Charter School Enrollment Percentage	2.1	2.5	0	21.9

Note: Spending per pupil, fund balance, and median income are in real (2013) dollars. See the note in the text regarding adjustments for the 2013 and 2014 value-added estimates.

Table 4. First Stage Results

	One Lag	Two Lags	
	Forecast Error, t-1	Forecast Error, t-1	Forecast Error, t-2
Deviation from Trend, t-1	0.234**	0.247**	-0.215**
	(0.0239)	(0.0278)	(0.0254)
Deviation from Trend, t-2		0.0626**	0.202**
		(0.0130)	(0.0259)
Log Spending Per Pupil	-1.732	-2.269*	-4.276**
	(0.942)	(1.048)	(0.826)
Percent Economically Disadvantaged	-0.0150	-0.0176	-0.00513
	(0.0151)	(0.0160)	(0.0136)
Log Median Income	-7.718**	-4.859	-3.541
	(2.789)	(3.316)	(3.180)
Tax Effort	-3.734**	-3.265**	-2.360*
	(0.671)	(0.764)	(1.024)
Percent Non White	-0.0410	-0.112	0.00323
	(0.0641)	(0.0808)	(0.0717)
Percent Limited English Proficiency	-0.0394	0.0772	-0.115
	(0.130)	(0.133)	(0.168)
Observations	4,237	3,630	3,630
Number of Districts	608	608	608
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Note. The table presents first-stage results for a 2SLS model that includes only one lag of forecast error (the first column) and one that includes two lags of forecast error (the second and third columns). The second and third columns correspond to equations 2 and 3 in the text and capture our preferred specification. Standard errors are clustered at the district level. The Angrist-Pischke F test statistics are 96.8 and 128.7 for the first and second lag respectively. ** $p<0.01$, * $p<0.05$.

Table 5. Main Results Without Covariates. Impact of Forecast Error On Annual School District Value-Added

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-0.000129	1.41e-05			-0.00128	-0.00382**
	(0.000397)	(0.000473)			(0.00102)	(0.00141)
Forecast Error, t-2		-0.000755				-0.00249*
		(0.000442)				(0.00114)
Deviation, t-1			-0.000305	-0.000442		
			(0.000241)	(0.000274)		
Deviation, t-2				-0.000771**		
				(0.000296)		
Observations	4,241	3,633	4,241	3,633	4,241	3,633
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Column 6 presents the specification from equation 4, except that it excludes the controls. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table 6. Main Results. Impact of Forecast Error On Annual School District Value-Added

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-6.84e-05	6.82e-05			-0.00127	-0.00395**
	(0.000399)	(0.000478)			(0.00105)	(0.00149)
Forecast Error, t-2		-0.000721				-0.00255*
		(0.000446)				(0.00117)
Deviation, t-1			-0.000297	-0.000423		
			(0.000241)	(0.000275)		
Deviation, t-2				-0.000763*		
				(0.000300)		
Log Spending Per Pupil	0.0256	0.0132	0.0266	0.0172	0.0244	-0.00272
	(0.0209)	(0.0236)	(0.0209)	(0.0235)	(0.0209)	(0.0254)
% Econ. Disad.	-0.000306	-0.000172	-0.000309	-0.000190	-0.000328	-0.000272
	(0.000286)	(0.000332)	(0.000286)	(0.000332)	(0.000286)	(0.000348)
Log Median Income	-0.0208	-0.0836	-0.0218	-0.0937	-0.0317	-0.122
	(0.0551)	(0.0669)	(0.0549)	(0.0670)	(0.0553)	(0.0674)
Tax Effort	0.0174	0.00921	0.0159	0.00399	0.0112	-0.0149
	(0.0170)	(0.0212)	(0.0168)	(0.0211)	(0.0174)	(0.0233)
% Non White	-0.00170	-0.000763	-0.00173	-0.000931	-0.00178	-0.00137
	(0.00116)	(0.00150)	(0.00116)	(0.00151)	(0.00116)	(0.00156)
% Lim. Eng. Prof.	-0.00301	-0.00526	-0.00299	-0.00507	-0.00304	-0.00505
	(0.00216)	(0.00292)	(0.00215)	(0.00292)	(0.00215)	(0.00294)
Observations	4,237	3,630	4,237	3,630	4,237	3,630
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table 7. Impact of Forecast Error On Annual School District Value-Added, by Grade Level

	(1) Grade 4	(2) Grade 5	(3) Grade 6	(4) Grade 7	(5) Grade 8
Forecast Error, t-1	-0.00476	-0.00703**	-0.000136	-0.00329	-0.00439
	(0.00244)	(0.00249)	(0.00259)	(0.00227)	(0.00281)
Forecast Error, t-2	-0.00402*	-0.00239	-0.000944	-0.00266	-0.00254
	(0.00169)	(0.00180)	(0.00162)	(0.00166)	(0.00194)
Observations	3,634	3,638	3,637	3,638	3,631
Number of Dist_IRN	608	608	608	608	608
Covariates	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variable is annual student value-added. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table 8. IV/2SLS Estimates of the Impact of Forecast Error on District Value-Added

	(1)	(2)
Forecast Error, t+1	-0.00127	-0.00140
	(0.00161)	(0.00162)
Forecast Error, t	-0.00147	-0.00171
	(0.00159)	(0.00167)
Forecast Error, t-1	-0.00262†	-0.00293†
	(0.00139)	(0.00152)
Forecast Error, t-2	-0.00308**	-0.00320**
	(0.00116)	(0.00119)
Observations	3,034	3,032
Number of Districts	607	607
Covariates	No	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. The dependent variable is annual student value-added. Standard errors are clustered at the district level. ** p<0.01, * p<0.05. † <0.10.

Table 9. IV/2SLS Estimates of the Impact of Predicted Revenue Deviation on Value-Added

	(1)	(2)
Deviation from Trend, t-1	-0.000496	-0.000501
	(0.000374)	(0.000375)
Deviation from Trend, t-2	-0.000528	-0.000541
	(0.000339)	(0.000344)
Observations	3,633	3,630
Number of Districts	608	608
Covariates	No	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. The dependent variable is annual student value-added. The estimates comes from the 2SLS models as specified in equation 8. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table 10. Shortfalls. IV/2SLS Estimates of the Impact of Shortfalls (Forecast Error ≥ 0) on District Value -Added

	(1)	(2)	(3)	(4)
	$\mathbf{1}(\text{FE} \geq 0)$	$\mathbf{1}(\text{FE} \geq 0)$	$\text{FE} \geq 0$	$\text{FE} \geq 0$
Shortfall, t-1	-0.0519**	-0.0514*	-0.0215*	-0.0224*
	(0.0198)	(0.0204)	(0.00976)	(0.0106)
Shortfall, t-2	-0.0330*	-0.0332*	-0.00944*	-0.00968*
	(0.0146)	(0.0148)	(0.00163)	(0.00449)
Observations	3,633	3,630	3,630	3,630
Number of Districts	608	608	608	608
Covariates	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. Columns 1 and 2 present the results of 2SLS models where forecast error is recoded as a binary variable so that it equals 1 when the error is positive (a shortfall) and zero otherwise. Columns 3 and 4 presents results where forecast error is recoded as zero when it is negative but otherwise left to vary continuously. Standard errors are clustered at the district level.** $p<0.01$, * $p<0.05$.

Table 11. IV/2SLS Estimates of the Impact of Forecast Error on Teacher Attrition and Levy Proposal

	(1) Teacher Attrition	(2) Teacher Attrition	(3) New Levy	(4) New Levy	(5) Replacement Levy	(6) Replacement Levy
Forecast Error, t-1	0.193**	0.169*	0.00974**	0.00795**	-0.000447	0.000785
	(0.0712)	(0.0752)	(0.00270)	(0.00281)	(0.00300)	(0.00322)
Forecast Error, t-2	0.107	0.100	0.00334	0.00270	-0.00260	-0.00214
	(0.0590)	(0.0591)	(0.00203)	(0.00205)	(0.00221)	(0.00228)
Observations	3,632	3,629	3,644	3,641	3,644	3,641
Number of Districts	608	608	608	608	608	608
Covariates	No	Yes	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variables are the percentage of teachers who are no longer in the district they were in last year, and a binary variable indicating whether new or replacement levy revenues were included in the forecast. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table 12. Heterogeneity. IV/2SLS Estimates of the Impact of Forecast Error on District Value-Added

	High Fund Bal. (1)	Low Fund Bal. (2)	High Enrollment (3)	Low Enrollment (4)
Forecast Error, t-1	-0.00214	-0.00680*	-0.00702*	-0.00278
	(0.00171)	(0.00269)	(0.00320)	(0.00159)
Forecast Error, t-2	-0.00148	-0.00362*	-0.00323	-0.00210
	(0.00157)	(0.00176)	(0.00195)	(0.00145)
Log Spending Per Pupil	0.0546	-0.0341	0.00260	-0.0168
	(0.0426)	(0.0292)	(0.0370)	(0.0444)
Percent Economically Disadvantaged	-0.000189	-0.000188	-8.04e-05	-0.000400
	(0.000428)	(0.000526)	(0.000442)	(0.000504)
Log Median Income	-0.0712	-0.205*	-0.193	-0.0962
	(0.0928)	(0.103)	(0.122)	(0.0844)
Tax Effort	0.00378	-0.0555	-0.0687	-0.00433
	(0.0299)	(0.0394)	(0.0406)	(0.0289)
Percent Non White	-0.000695	-0.00190	-0.00228	0.000488
	(0.00227)	(0.00238)	(0.00229)	(0.00242)
Percent Limited English Proficiency	-0.000779	-0.00981*	-0.00418	-0.00365
	(0.00378)	(0.00426)	(0.00356)	(0.00542)
Observations	1,813	1,817	1,818	1,812
Number of Districts	304	304	304	304
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. All columns present the results of 2SLS models as specified in equation 4, estimated using a subsample of districts. Fund balances were scaled by district revenues. A high/low fund balance indicates that the district's average fund balance over the sample period was above/below the median of 22.2 percent. A high/low fund enrollment indicates that the district's average enrollment over the sample period was above/below the median of 1,732. To test the significance of the difference in the estimates between high/low fund balance (p=0.054) and high/low enrollment (p=0.124), we drew 500 bootstrapped samples. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

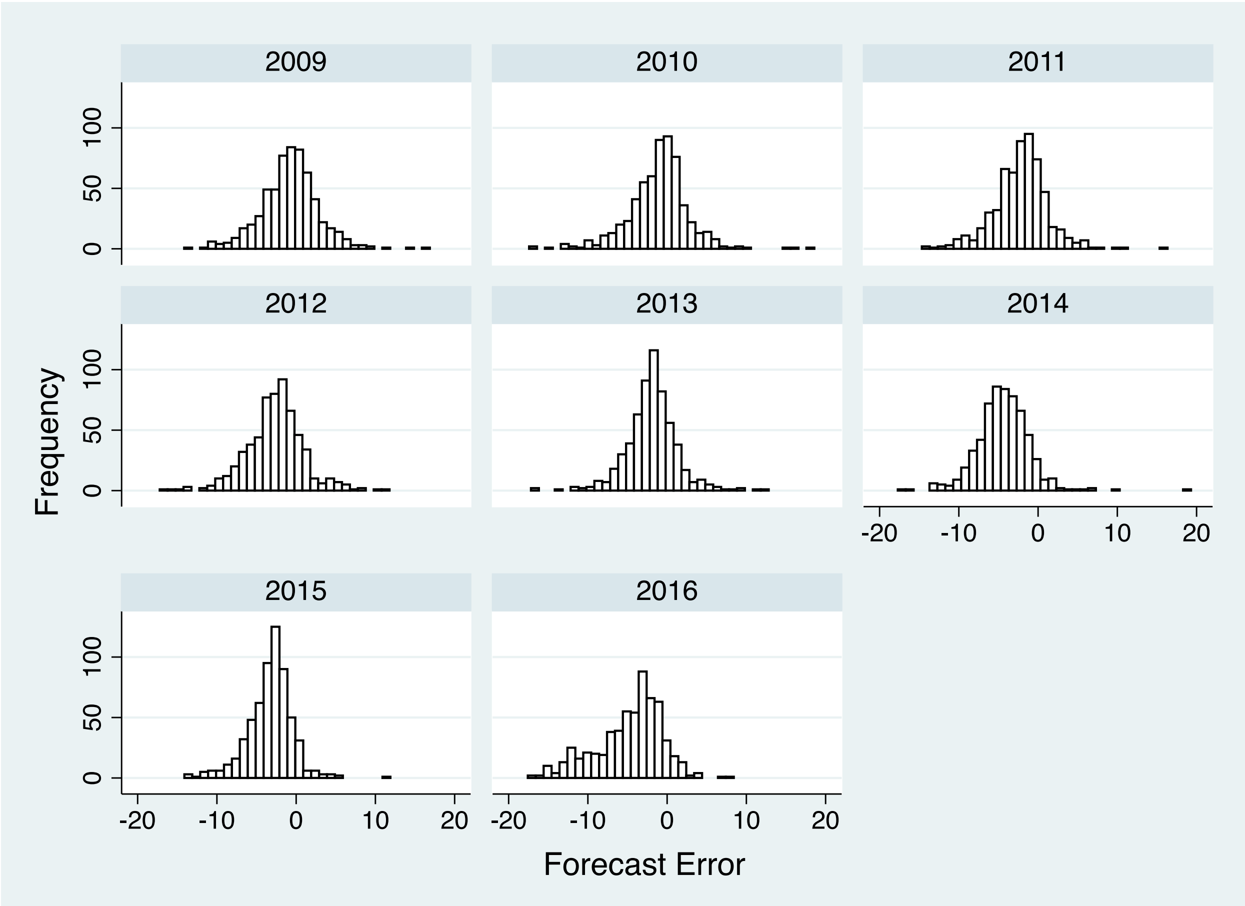
Table 13. Heterogeneity. IV/2SLS Estimates of the Impact of Forecast Error on District Value-Added

	Urban/ Non-rural	Rural	High Charter Enrollment	Low Charter Enrollment
	(1)	(2)	(3)	(4)
Forecast Error, t-1	-0.00642**	-0.000459	-0.00450	-0.00315
	(0.00231)	(0.00188)	(0.00235)	(0.00171)
Forecast Error, t-2	-0.00381**	-0.000514	-0.00164	-0.00333*
	(0.00144)	(0.00176)	(0.00159)	(0.00160)
Log Spending Per Pupil	0.00514	0.00798	0.0447	-0.0236
	(0.0399)	(0.0289)	(0.0421)	(0.0246)
Percent Economically Disadvantaged	-0.000152	-0.000158	-0.000218	-0.000306
	(0.000375)	(0.000583)	(0.000367)	(0.000704)
Log Median Income	-0.0879	-0.138	-0.106	-0.179
	(0.113)	(0.0919)	(0.0984)	(0.0962)
Tax Effort	-0.0537	-0.0175	-0.0480	0.0127
	(0.0405)	(0.0300)	(0.0322)	(0.0318)
Percent Non White	-0.00171	0.000767	-0.00174	0.000845
	(0.00197)	(0.00383)	(0.00201)	(0.00266)
Percent Limited English Proficiency	-0.00480	-0.00200	-0.00281	-0.00777
	(0.00352)	(0.00466)	(0.00360)	(0.00535)
Observations	2,257	1,373	1,851	1,799
Number of Districts	378	230	308	300
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. All columns present the results of 2SLS models as specified in equation 4, estimated using a subsample of districts. A high charter enrollment indicates that the percentage of students in the districts enrolled in charter schools was higher than the median of 1.44%. To test the significance of the difference in the estimates between rural and non-rural (p=0.018), we drew 500 bootstrapped samples. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

A Appendix

Figure A1: Forecast Error by Year



Note: The histogram presents the number of districts with forecast errors of a particular size by year. The mean and standard deviation (respectively) of forecast error by year are as follows: 2009 (-0.7, 3.7), 2010(-1.2, 4.2), 2011(-2.2, 3.4), 2012(-2.6, 3.8), 2013(-2.0, 3.4), 2014(-4.5, 3.5), 2015(-3.3, 3.6), 2016(-4.8,4.3).

Table A1. Without Controlling for Spending. Impact of Forecast Error On Annual School District Value-Added

VARIABLES	(1) District Value-Added	(2) District Value-Added
Forecast Error, t-1	-0.00122	-0.00399**
	(0.00105)	(0.00150)
Forecast Error, t-2		-0.00260*
		(0.00116)
Percent Economically Disadvantaged	-0.000375	-0.000319
	(0.000277)	(0.000342)
Log Median Income	-0.0252	-0.122
	(0.0551)	(0.0669)
Tax Effort	0.0134	-0.0145
	(0.0175)	(0.0234)
Percent Non White	-0.00181	-0.00128
	(0.00117)	(0.00156)
Percent Limited English Proficiency	-0.00315	-0.00499
	(0.00215)	(0.00292)
Observations	4,241	3,633
Number of Districts	608	608
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variable is annual student value-added. The table is identical to columns 5 and 6 in Table 6 except that spending is not included as a covariate. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A2. Impact of Forecast Error On School District Performance Index

VARIABLES	(1) Performance Index	(2) Performance Index
Forecast Error, t-1	-0.00240	-0.00273
	(0.00501)	(0.00535)
Forecast Error, t-1	4.15e-06	-0.000449
	(0.00352)	(0.00363)
Observations	3,644	3,641
Number of Districts	608	608
Covariates	No	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variable is the school district performance index, which has been standardized by year so that the units are in standard deviations. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table A3. Impact of Forecast Error On Annual School District Value-Added (Math Only)

	(1) Grade 4 Math	(2) Grade 5 Math	(3) Grade 6 Math	(4) Grade 7 Math	(5) Grade 8 Math
Forecast Error, t-1	-0.00756*	-0.00695*	0.000384	-0.00240	-0.00511
	(0.00303)	(0.00306)	(0.00326)	(0.00286)	(0.00385)
Forecast Error, t-2	-0.00580**	-0.00297	-0.000713	-0.00394	-0.00328
	(0.00207)	(0.00215)	(0.00210)	(0.00202)	(0.00215)
Observations	3,634	3,638	3,637	3,638	3,626
Number of Districts	608	608	608	608	608
Covariates	Yes	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Note. All columns present the results of 2SLS models.The dependent variable is annual student value-added. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table A4. Scaling Deviations by Current Year Revenues. Main Results Without Covariates.

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-0.000129	1.41e-05			-0.00118	-0.00389**
	(0.000397)	(0.000473)			(0.00101)	(0.00141)
Forecast Error, t-2		-0.000755				-0.00262*
		(0.000442)				(0.00113)
Deviation from Trend, t-1			-0.000280	-0.000427		
			(0.000238)	(0.000270)		
Deviation from Trend, t-2				-0.000791**		
				(0.000290)		
Observations	4,241	3,633	4,241	3,633	4,241	3,633
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table is similar to Table 5 in the main text except that the deviation from trend has been scaled by the current year's revenues rather than the previous year's. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Column 6 presents the specification from equation 4, except that it excludes the controls. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A5. Scaling Deviations by Current Year Revenues. Main Results.

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-6.84e-05	6.82e-05			-0.00117	-0.00402**
	(0.000399)	(0.000478)			(0.00103)	(0.00150)
Forecast Error, t-2		-0.000721				-0.00269*
		(0.000446)				(0.00116)
Deviation, t-1			-0.000273	-0.000408		
			(0.000238)	(0.000272)		
Deviation, t-2				-0.000785**		
				(0.000294)		
Log Spending Per Pupil	0.0256	0.0132	0.0265	0.0171	0.0245	-0.00351
	(0.0209)	(0.0236)	(0.0209)	(0.0235)	(0.0209)	(0.0254)
% Econ. Disad.	-0.000306	-0.000172	-0.000309	-0.000190	-0.000326	-0.000274
	(0.000286)	(0.000332)	(0.000286)	(0.000332)	(0.000286)	(0.000350)
Log Median Income	-0.0208	-0.0836	-0.0214	-0.0930	-0.0308	-0.123
	(0.0551)	(0.0669)	(0.0549)	(0.0671)	(0.0554)	(0.0676)
Tax Effort	0.0174	0.00921	0.0162	0.00435	0.0117	-0.0155
	(0.0170)	(0.0212)	(0.0168)	(0.0211)	(0.0174)	(0.0233)
% Non White	-0.00170	-0.000763	-0.00173	-0.000941	-0.00177	-0.00138
	(0.00116)	(0.00150)	(0.00116)	(0.00151)	(0.00116)	(0.00157)
% Lim. Eng. Prof.	-0.00301	-0.00526	-0.00299	-0.00507	-0.00304	-0.00507
	(0.00216)	(0.00292)	(0.00215)	(0.00292)	(0.00215)	(0.00294)
Observations	4,237	3,630	4,237	3,630	4,237	3,630
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table is similar to Table 6 in the main text except that the deviation from trend has been scaled by the current year's revenues rather than the previous year's. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A6. Scaling Deviations by Current Year Revenues. Shortfalls.

	(1) $\mathbf{1}(\text{FE} \geq 0)$	(2) $\mathbf{1}(\text{FE} \geq 0)$	(3) $\text{FE} \geq 0$	(4) $\text{FE} \geq 0$
Shortfall, t-1	-0.0510**	-0.0506*	-0.0209*	-0.0217*
	(0.0193)	(0.0199)	(0.00966)	(0.0104)
Shortfall, t-2	-0.0343*	-0.0347*	-0.00979*	-0.0101*
	(0.0144)	(0.0146)	(0.00426)	(0.00441)
Observations	3,633	3,630	3,633	3,630
Number of Districts	608	608	608	608
Covariates	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. This table is similar to Table 10 in the main text except that the deviation from trend has been scaled by the current year's revenues rather than the previous year's. The dependent variable is annual student value-added. Columns 1 and 2 present the results of 2SLS models where forecast error is recoded as a binary variable so that it equals 1 when the error is positive (a shortfall) and zero otherwise. Columns 3 and 4 presents results where forecast error is recoded as zero when it is negative but otherwise left to vary continuously. Standard errors are clustered at the district level.** $p<0.01$, * $p<0.05$.

Table A7. Using Four Years of Revenues to Calculate the Deviation from Trend. Main Results Without Covariates.

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-0.000129	1.41e-05			-0.00153	-0.00227*
	(0.000397)	(0.000473)			(0.000892)	(0.00107)
Forecast Error, t-2		-0.000755				-0.00161
		(0.000442)				(0.000989)
Deviation from Trend, t-1			-0.000430	-0.000358		
			(0.000249)	(0.000289)		
Deviation from Trend, t-2				-0.000535		
				(0.000300)		
Observations	4,241	3,633	4,241	3,633	4,241	3,633
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table is similar to Table 5 in the main text except that the prior revenue trend has been calculated using four years of revenues rather than three. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Column 6 presents the specification from equation 4, except that it excludes the controls. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A8. Using Four Years of Revenues to Calculate the Deviation from Trend. Main Results.

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	-6.84e-05	6.82e-05			-0.00154	-0.00232*
	(0.000399)	(0.000478)			(0.000914)	(0.00113)
Forecast Error, t-2		-0.000721				-0.00164
		(0.000446)				(0.00101)
Deviation from Trend, t-1			-0.000423	-0.000344		
			(0.000250)	(0.000291)		
Deviation from Trend, t-2				-0.000531		
				(0.000303)		
Log Spending Per Pupil	0.0256	0.0132	0.0270	0.0169	0.0241	0.00458
	(0.0209)	(0.0236)	(0.0209)	(0.0235)	(0.0209)	(0.0242)
% Econ. Disad.	-0.000306	-0.000172	-0.000313	-0.000184	-0.000333	-0.000231
	(0.000286)	(0.000332)	(0.000286)	(0.000334)	(0.000287)	(0.000339)
Log Median Income	-0.0208	-0.0836	-0.0239	-0.0909	-0.0340	-0.106
	(0.0551)	(0.0669)	(0.0549)	(0.0669)	(0.0551)	(0.0664)
Tax Effort	0.0174	0.00921	0.0147	0.00465	0.00983	-0.00486
	(0.0170)	(0.0212)	(0.0169)	(0.0212)	(0.0173)	(0.0221)
% Non White	-0.00170	-0.000763	-0.00178	-0.000936	-0.00180	-0.00112
	(0.00116)	(0.00150)	(0.00116)	(0.00150)	(0.00116)	(0.00152)
% Lim. Eng. Prof.	-0.00301	-0.00526	-0.00301	-0.00514	-0.00305	-0.00511
	(0.00216)	(0.00292)	(0.00215)	(0.00292)	(0.00215)	(0.00290)
Observations	4,237	3,630	4,237	3,630	4,237	3,630
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table is similar to Table 6 in the main text except that the prior revenue trend has been calculated using four years of revenues rather than three. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A9. Using Four Years of Revenues to Calculate the Deviation from Trend. Shortfalls.

	(1)	(2)	(3)	(4)
	$\mathbf{1}(\text{FE} \geq 0)$	$\mathbf{1}(\text{FE} \geq 0)$	$\text{FE} \geq 0$	$\text{FE} \geq 0$
Shortfall, t-1	-0.0328*	-0.0323	-0.0114*	-0.0117*
	(0.0166)	(0.0171)	(0.00543)	(0.00580)
Shortfall, t-2	-0.0230	-0.0231	-0.00515	-0.00526
	(0.0131)	(0.0133)	(0.00343)	(0.00351)
Observations	3,633	3,630	3,633	3,630
Number of Districts	608	608	608	608
Covariates	No	Yes	No	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. This table is similar to Table 10 in the main text except that the prior revenue trend has been calculated using four years of revenues rather than three. The dependent variable is annual student value-added. Columns 1 and 2 present the results of 2SLS models where forecast error is recoded as a binary variable so that it equals 1 when the error is positive (a shortfall) and zero otherwise. Columns 3 and 4 presents results where forecast error is recoded as zero when it is negative but otherwise left to vary continuously. Standard errors are clustered at the district level.** $p<0.01$, * $p<0.05$.

Table A10. Excluding Observations with Proposed Levy Revenue. Impact of Forecast Error On Annual School District Value-Added

VARIABLES	(1) District Value-Added	(2) District Value-Added
Forecast Error, t-1	-0.00134	-0.00466*
	(0.00120)	(0.00189)
Forecast Error, t-2		-0.00334*
		(0.00141)
Log Spending Per Pupil	0.0251	-0.000346
	(0.0236)	(0.0300)
Percent Economically Disadvantaged	-0.000453	-0.000469
	(0.000324)	(0.000413)
Log Median Income	-0.00277	-0.134
	(0.0666)	(0.0880)
Tax Effort	0.0162	-0.0126
	(0.0202)	(0.0298)
Percent Non White	-0.00216	-0.00213
	(0.00139)	(0.00208)
Percent Limited English Proficiency	-0.00412	-0.00821*
	(0.00268)	(0.00386)
Observations	3,649	2,889
Number of Districts	603	566
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variable is annual student value-added. Observations in which a district includes potential levy revenue in its revenue forecast are excluded. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table A11. Shortfalls and Possible Mechanisms. IV/2SLS Estimates of the Impact of a Shortfall on Teacher Attrition and Levy Proposal.

	(1) Teacher Attrition	(2) New Levy	(3) Teacher Attrition	(4) New Levy
Shortfall, t-1	2.213*	0.110**	0.889	0.0397*
	(1.023)	(0.0369)	(0.454)	(0.0174)
Shortfall, t-2	1.298	0.0366	0.354	0.00923
	(0.724)	(0.0260)	(0.219)	(0.00804)
Observations	3,629	3,641	3,629	3,641
Number of Districts	608	608	608	608
Covariates	Yes	Yes	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variables are the percentage of teachers who are no longer in the district they were in last year, and a binary variable indicating whether a levy was on the ballot. Columns 1 and 2 present the results of 2SLS models where forecast error is recoded as a binary variable so that it equals 1 when the error is positive (a shortfall) and zero otherwise. Columns 3 and 4 presents results where forecast error is recoded as zero when it is negative but otherwise left to vary continuously. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Appendix Table A12. IV/2SLS Estimates of the Impact of Forecast Error on Teacher Count and Student-Teacher Ratios

	(1) Percent Change Teacher Count	(2) Percent Change Student-Teacher Ratio
Forecast Error, t-1,	-0.243*	0.307*
	(0.123)	(0.151)
Forecast Error, t-2,	-0.154*	0.148
	(0.0731)	(0.0896)
Observations	3,632	3,632
Number of Districts	608	608
Covariates	Yes	Yes
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. All columns present the results of 2SLS models. The dependent variables are the change in district teacher counts and student-teacher ratios. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A13. Shortfalls and Changes in Spending. IV/2SLS Estimates of the Impact of Shortfalls on Spending Categories.

	(1) Log Total Expend.	(2) Log Instr. Expend.	(3) Log Admin. Expend.	(4) Log Total Expend.	(5) Log Instr. Expend.	(6) Log Admin. Expend.
Shortfall, t-1	-0.0395	-0.0174	0.0538	-0.0152	-0.00679	0.0188
	(0.0241)	(0.0164)	(0.0327)	(0.0103)	(0.00626)	(0.0138)
Shortfall, t-2	-0.0224	-0.0105	0.0179	-0.00611	-0.00282	0.00445
	(0.0175)	(0.00822)	(0.0158)	(0.00504)	(0.00241)	(0.00459)
Observations	3,641	3,639	3,640	3,641	3,639	3,640
Number of Districts	608	608	608	608	608	608
Covariates	No	No	No	No	No	No
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. All columns present the results of 2SLS models.The dependent variables are the log total spending, log instructional spending, and log administrative spending. Columns 1-3 present the results of 2SLS models where forecast error is recoded as a binary variable so that it equals 1 when the error is positive (a shortfall) and zero otherwise. Columns 4-6 presents results where forecast error is recoded as zero when it is negative but otherwise left to vary continuously. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A14. Using 2008 fund balance to split sample.(Only first two columns are replaced). Heterogeneity. IV/2SLS Estimates of the Impact of Forecast Error on District Value-Added

	High Fund Bal. (1)	Low Fund Bal. (2)	High Enrollment (3)	Low Enrollment (4)
Forecast Error, t-1	-0.00312	-0.00594*	-0.00702*	-0.00278
	(0.00165)	(0.00299)	(0.00320)	(0.00159)
Forecast Error, t-2	-0.00128	-0.00437*	-0.00323	-0.00210
	(0.00156)	(0.00172)	(0.00195)	(0.00145)
Log Spending Per Pupil	0.0320	-0.0247	0.00260	-0.0168
	(0.0420)	(0.0317)	(0.0370)	(0.0444)
Percent Economically Disadvantaged	-0.000760	0.000287	-8.04e-05	-0.000400
	(0.000494)	(0.000489)	(0.000442)	(0.000504)
Log Median Income	-0.0554	-0.178	-0.193	-0.0962
	(0.0988)	(0.0957)	(0.122)	(0.0844)
Tax Effort	-0.0179	-0.0237	-0.0687	-0.00433
	(0.0317)	(0.0366)	(0.0406)	(0.0289)
Percent Non White	0.000280	-0.00274	-0.00228	0.000488
	(0.00240)	(0.00230)	(0.00229)	(0.00242)
Percent Limited English Proficiency	-0.00400	-0.00820	-0.00418	-0.00365
	(0.00394)	(0.00456)	(0.00356)	(0.00542)
Observations	1,813	1,817	1,818	1,812
Number of Districts	304	304	304	304
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. All columns present the results of 2SLS models as specified in equation 4, estimated using a subsample of districts. Fund balances were scaled by district revenues. A high/low fund balance indicates that the district's fund balance in 2008 was above/below the median of 19.5 percent. A high/low enrollment indicates that the district's average enrollment over the sample period was above/below the median of 1,732. To test the significance of the difference in the estimates between high/low fund balance (p=0.22 for first lag, p = 0.086 for 2nd lag) and high/low enrollment (p=0.124 for first lag), we drew 500 bootstrapped samples. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.

Table A15. Splitting fund balance into thirds to examine monotonicity.

	Bottom 1/3 Fund Bal. (1)	Middle 1/3 Fund Bal. (2)	Top 1/3 Fund Bal. (3)
Forecast Error, t-1	-0.00625	-0.00420	-0.00225
	(0.00384)	(0.00225)	(0.00192)
Forecast Error, t-2	-0.00234	-0.00546*	0.000106
	(0.00209)	(0.00242)	(0.00163)
Log Spending Per Pupil	-0.0129	-0.0624	0.0761
	(0.0333)	(0.0613)	(0.0493)
Percent Economically Disadvantaged	0.000210	-0.000648	-8.95e-05
	(0.000525)	(0.000726)	(0.000500)
Log Median Income	-0.228	-0.0438	-0.101
	(0.130)	(0.127)	(0.112)
Tax Effort	-0.0473	0.0127	-0.0292
	(0.0499)	(0.0386)	(0.0372)
Percent Non White	-0.00232	-0.00295	0.000370
	(0.00280)	(0.00276)	(0.00284)
Percent Limited English Proficiency	-0.0110**	0.000571	-0.00585
	(0.00377)	(0.00419)	(0.00691)
Observations	1,212	1,212	1,206
Number of Districts	203	203	202
District Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Note. The dependent variable is annual student value-added. All columns present the results of 2SLS models as specified in equation 4, estimated using a subsample of districts. The first column presents the results for fund balances in the bottom third of the distribution (< 16%). The middle column presents the results for fund balances in the middle third (> 16%, < 29%). The third column presents results for fund balances in the top third (> 29%). Fund balances were scaled by district revenues. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table A16. Dropping first two years. Main Results.

	OLS		Reduced Form/OLS		IV/2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Error, t-1	8.31e-05	0.000378			-0.00171	-0.00592**
	(0.000613)	(0.000796)			(0.00143)	(0.00201)
Forecast Error, t-2		-0.000895				-0.00376
		(0.000733)				(0.00195)
Deviation, t-1			-0.000416	-0.000843*		
			(0.000347)	(0.000427)		
Deviation, t-2				-0.00118*		
				(0.000483)		
Log Spending Per Pupil	0.0154	0.0168	0.0162	0.0114	0.0159	-0.0103
	(0.0273)	(0.0499)	(0.0272)	(0.0494)	(0.0273)	(0.0541)
% Econ. Disad.	-0.000212	-0.000328	-0.000232	-0.000360	-0.000268	-0.000487
	(0.000412)	(0.000486)	(0.000411)	(0.000481)	(0.000416)	(0.000510)
Log Median Income	-0.0748	-0.120	-0.0787	-0.147	-0.0839	-0.201
	(0.0824)	(0.111)	(0.0821)	(0.111)	(0.0810)	(0.115)
Tax Effort	0.0200	0.00932	0.0169	-0.00209	0.0120	-0.0219
	(0.0263)	(0.0349)	(0.0260)	(0.0349)	(0.0263)	(0.0364)
% Non White	-0.00123	-0.00430	-0.00137	-0.00515	-0.00161	-0.00555
	(0.00201)	(0.00288)	(0.00202)	(0.00287)	(0.00204)	(0.00308)
% Limited Eng. Prof.	-0.00728	-0.00974	-0.00725	-0.00944	-0.00724	-0.00952
	(0.00402)	(0.00597)	(0.00400)	(0.00594)	(0.00397)	(0.00580)
Observations	3,023	2,417	3,023	2,417	3,023	2,417
Number of Districts	608	608	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note. This table is similar to Table 6 in the main text except that the first two years (FY 2009 and FY 2010) have been dropped from the sample. The dependent variable is annual student value-added. The first four columns present the results from OLS models. The last two columns present the results of 2SLS models. Standard errors are clustered at the district level. ** p<0.01, * p<0.05.

Table A17. Heterogeneity by Recession Intensity and Charter School Enrollment. IV/2SLS Estimates of the Impact of Forecast Error on District Value-Added

	High Recession Intensity (1)	Low Recession Intensity (2)
Forecast Error, t-1	-0.00126	-0.00573*
	(0.00182)	(0.00233)
Forecast Error, t-2	-0.00168	-0.00260
	(0.00161)	(0.00150)
Log Spending Per Pupil	0.0292	-0.0175
	(0.0350)	(0.0313)
Percent Economically Disadvantaged	3.45e-05	-0.000430
	(0.000474)	(0.000457)
Log Median Income	-0.0833	-0.133
	(0.102)	(0.0925)
Tax Effort	0.00135	-0.0578
	(0.0306)	(0.0460)
Percent Non White	-0.00194	-2.82e-05
	(0.00202)	(0.00166)
Percent Limited English Proficiency	-0.0104*	-0.00115
	(0.00457)	(0.00361)
Observations	1,815	1,787
Number of Districts	303	297
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. The dependent variable is annual student value-added. All columns present the results of 2SLS models as specified in equation 4, estimated using a subsample of districts. A high recession intensity indicates that the district was in a county that experienced higher than the median percentage point increase in the unemployment rate (5.45%) during the recession (2007-2009). Standard errors are clustered at the county level. ** $p<0.01$, * $p<0.05$.

Table A18. Demographic Covariates as Dependent Variables.

	(1) % Econ. Disad.	(2) % Non-White	(3) %LEP	(4) Log Enrollment
Forecast Error, t-1	-0.136	-0.0208	0.0106	-0.000616
	(0.0891)	(0.0197)	(0.0102)	(0.000866)
Forecast Error, t-2	-0.0229	-0.0154	-0.00180	-0.000358
	(0.0562)	(0.00983)	(0.00582)	(0.000529)
Observations	3,644	3,644	3,644	3,644
Number of Districts	608	608	608	608
District Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Note. This table presents results from 2SLS models where the dependent variables are demographic covariates rather than student value-added. None of the estimates are significant, even at the 10 percent level. Standard errors are clustered at the district level.** $p<0.01$, * $p<0.05$.

Table A19. Controlling for Deviations from Enrollment Trends

VARIABLES	(1) District Value-Added	(2) District Value-Added
Forecast Error, t-1	-0.00128	-0.00398**
	(0.00104)	(0.00150)
Forecast Error, t-2		-0.00256*
		(0.00117)
Log Spending Per Pupil	0.0249	0.000315
	(0.0216)	(0.0264)
Percent Economically Disadvantaged	-0.000327	-0.000270
	(0.000286)	(0.000349)
Log Median Income	-0.0319	-0.123
	(0.0554)	(0.0676)
Tax Effort	0.0110	-0.0159
	(0.0174)	(0.0235)
Percent Non White	-0.00178	-0.00136
	(0.00116)	(0.00156)
Percent Limited English Proficiency	-0.00305	-0.00505
	(0.00216)	(0.00294)
Deviation from Enrollment Trend	-3.58e-05	-0.000190
	(0.000306)	(0.000347)
Observations	4,237	3,630
Number of Districts	608	608
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Note. This table is similar to the last two columns from Table 6 (IV/2SLS) in the main text except that the deviation in enrollment trends is included as an additional covariate. The dependent variable is annual student value-added. Standard errors are clustered at the district level. ** $p<0.01$, * $p<0.05$.