More Than Money: Local Fiscal Choice and Student Achievement After Funding Reform

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Abstract

This study examines the impact of repealing adequacy-based funding on student test scores in poorer school districts. Contrary to expectations, scores improved for two years post-repeal. We explored local spending as a possible reason. Despite funding cuts, poorer districts increased spending on student support services like counseling and health services while reducing staff support and equipment expenses. This shift toward student well-being may have mitigated the negative effects of funding loss, resulting in unexpected test score gains. These findings highlight the importance of local discretion in resource allocation, showing that tailored spending can enhance educational outcomes even amid financial challenges.

Keywords: school aid, adequacy-based funding, outcome equity, asymmetric wealth effects

JEL Codes: I22, I24, I28, H52, H75

Introduction

Since the enaction of the Kentucky Education Reform Act (KERA) of 1990, many state governments have endeavored to equalize not only fiscal resources but also educational outcomes, across local school districts. This period since 1990, often referred to as the adequacy of education era, mandated state governments to prepare students to meet state-set educational performance standards through state aid to local school districts (Jackson, Johnson, & Persico, 2016; Candelaria & Shores, 2019). Many empirical studies, which are introduced in the next section, report that adequacy-based school aid to school districts significantly enhanced student performance. The improvement was more pronounced in poorer districts. However, these studies have yet to explore the effects of repealing adequacy-based school aid on student performance, especially within impoverished school districts. Filling this gap is crucial, as more than a decade has passed since Ohio repealed its form of adequacy-based aid, the PAthway to Student Success (PASS), at the close of FY 2011, and finally phased out its transitionary funding called, the Bridge Formula, at the end of FY2013. Ohio's PASS was distinctive for its focus on enhancing student performance and achieving outcome equity while maintaining provisions for fiscal equity (Ohio Legislative Service Commission, 2011).

This study provides compelling evidence that the repeal of Ohio's PASS program has significant implications for student performance, particularly for students attending schools in varying socioeconomic contexts. The research findings suggest that the repeal of the program yielded an unexpected positive impact on student performance in districts falling within the bottom 25 percent districts in terms of property valuation distribution two years post-repeal. This surprising outcome is attributed to the changes in local spending patterns. Despite facing adequacy-based funding cuts, poorer school districts shifted spending priorities. These districts increased investment in student support services, such as counseling, psychological or health services. Conversely, spending on staff support and equipment saw a decrease. The increased focus on student support services mitigated the negative effects of adequacy-based funding cuts. This, in turn, could have led to unexpected gains in student test scores, highlighting the potential benefits of prioritizing student well-being. These results underscore the crucial role of local discretion in resource allocation. By allowing districts to make tailored spending decisions, they can significantly enhance educational outcomes even when faced with funding challenges.

The next section provides the literature on adequacy-based aid and its impacts on educational outcome and outcome equity. The third section on the programmatic details of

Ohio's PASS provides the information necessary to investigate the impacts of its repeal. The section on data and model explains the variables used in Difference-in-Differences (DiD) estimation schemes for answering research questions in this paper. The section on findings and discussions provides key findings and their policy implications, followed by conclusions.

Impacts of Adequacy-based School Aid on Outcomes and Outcome Equity

Various empirical studies have shown that court-mandated school finance reforms (SFRs) substantially improved fiscal equity across local school districts in most states by around the early 1990s (Evans, Murray, & Schwab, 1997; Murray, Evans, & Schwab, 1998; Corcoran & Evans, 2015; Hoxby, 2001). However, since the Kentucky Education Reform Act (KERA) of 1990 opened the era of adequacy of education, state governments have attempted to ensure public education programs to prepare students for state performance standards. As a result, state governments have endeavored to equalize not just fiscal resources but educational attainment or student performance across local school districts (Jackson, Johnson, & Persico, 2016; Candelaria & Shores, 2019).

Even since 1990, many states have still pursued fiscal equity. According to Hyman (2017) and Cullen and Loeb (2004), Michigan's Proposal A of 1994 improved fiscal equity across school districts until the early 2000s. However, Hyman (2017) reported that Proposal A weakened outcome equity at the district level and fiscal equity at the school level. Downs (2004) indicated that Act 60 of 1997 in Vermont enhanced both fiscal and outcome equity at the school district level by 2002. However, fiscal equity somewhat deteriorated by 2011 (Picus, Goertz, & Odden, 2015). Lafortune, Rothstein and Schanzenbach (2018) analyzed sixty-four school finance reforms (SFRs) in twenty-six states during the adequacy of education era, which were based on either fiscal equity or adequacy of education. SFRs increased per pupil state aid mostly in the poorest income quintile school districts and student test scores significantly increased in under-performing districts that were likely to be poorer districts.

Some studies have narrowly focused on SFRs that were based on adequacy of education. In 1985, the New Jersey Supreme Court mandated the state legislature to equalize school funding across school districts. This adequacy-based approach improved fiscal equity between 1985 and 2008. However, the 2008 School Finance Reform Act dropped special funding for urban poor districts, leading to a widening spending disparity between them and wealthy districts (Picus, Goertz, & Odden, 2015).

Candelaria and Shores (2019) analyzed post-1990 SFRs in 13 states where states' education finance systems were ruled unconstitutional strictly based on adequacy of education grounds. They found that court-ordered adequacy-based reforms increased per pupil revenue in both the poorest and wealthiest quartile districts. Graduation rates increased by 11.5 percent in the poorest districts, with small effects for middle quartile districts and some modest effects for the wealthiest quartile districts. The study suggests that adequacy-based school finance reforms had stronger impacts on educational outcomes and outcome equity.

While previous research has explored how adequacy-based school funding reforms affect educational outcomes and outcome equity, no studies have yet investigated the effects of repealing such reforms to the best knowledge of this author. For example, Ohio was one of the states included in Candelaria and Shores (2019), which overturned states' education finance systems strictly based on adequacy of education grounds. However, Ohio repealed its version of adequacy-based funding at the end of FY 2011 and phased out its transitionary funding at the close of FY 2013. Since adequacy-based school funding has differential impacts on educational outcomes for wealthy and poor districts, it is reasonable to assume that repealing such funding would also have differing effects: poorer districts might suffer from stronger declines in student performance after repealing adequacy-based funding because they experienced relatively higher gains in student performance with adequacy-based funding. This study aims to examine how repealing the funding affects educational attainment in different districts.

Ohio's PAthway to Student Success (PASS)

Ohio has pursued an adequacy-based school funding system since the 1990s, following the Kentucky Education Reform Act (KERA) of 1990. In 1997, the Ohio Supreme Court declared that Ohio's public school funding system was unconstitutional due to its failure to provide an equitable and adequate base funding to meet academic goals. Subsequent court rulings in 2000, 2001, 2002, and 2003 affirmed the inadequacy of the education system (Johnson & Vesely, 2017; Simon, 2015; Obhof, 2005; Yazback, 2007; Sweetland, 2015). These court-ordered calls for adequacy-based school funding led Ohio to enact legislation adopting the Evidence-Based Model (EBM) approach to state aid formulas for local school districts in 2010. The evidence-based model (EBM) is one of the most frequently adopted adequacy-based school funding methods. It identifies and applies school-based programs and educational strategies shown to improve student learning. EBM also incorporates recommendations from state policy makers and educational leaders into its program details, which are detailed in recent studies (Odden, Picus, & Goetz, 2010; Odden, Goetz, & Picus, 2007; Odden & Picus, 2018; Picus, Odden, Glenn, Griffith, & Wolkoff, 2012; Picus, et al., 2013a; Picus, Odden, Goetz, Aportela, & Griffith, 2013b; Baker, Di Carlo, & Weber, 2022). As Table 3 illustrates, PASS funding differs from the funding formulas used prior to 2010, even though state aid formulas between 2002 and

2011 were adequacy-based. The PASS formulas, as detailed below, are grounded in evidence-based recommendations for educational performance.

During the FY 2010 and FY 2011, Ohio's EBM-based foundation funding system relied on the PAthway to Student Success (PASS) program, which has eight main funding components based on EBM strategies. The eight components included: Instructional Services Support, Additional Services Support, Administrative Services Support, Operations and Maintenance Support, Gifted Education and Enrichment Support, Technology Resources Support, Professional Development, and Instructional Materials (Ohio Legislative Service Commission 2011).

Foundation funding amounts in the PASS were determined using detailed computation formulas developed from previous research findings. For instance, Instructional Services Support (one of the above eight components), which constituted 63.5 percent of the total funding amounts, covered seven types of teachers such as core teachers, specialist teachers, etc. Core teachers specifically referred to educators who taught English Language Arts, mathematics, social studies, or foreign languages. One core teacher was assigned per 19 students for grades kindergarten through three and one teacher per 25 students for grades four through twelve in FY 2010 and FY 2011. Statewide, the model indicated that there were 77,341 core teachers in FY 2010, including 39,085 in elementary schools, 16,255 in middle schools, and 22,001 in high schools. Then, the number of other remaining six types of teachers was calculated in a similar manner. The number of teachers was based on some evidence from previous empirical research findings on the best student-to-teacher ratios for student performance. Finally, the compensation for one teacher was computed as the state-set compensation level multiplied by school district's educational challenge factor (ECF), which is explained below. For FY 2010, the compensation for one teacher was \$56902 * district's ECF. For FY 2011, that was \$57812 * district's ECF. The above methods were applied to all the eight main funding components in the PASS (Ohio Legislative Service Commission, 2011; Ohio Education Department, 2010a, 2010b).

The evidence-based approaches in the PASS funding formulas intended to enhance student performance as one can expect. At the same time, however, they were expected to improve fiscal equity as well. The amount of local revenue was computed as local property valuation multiplied by a uniform 22 mills. Then, the state made up the difference between the local share and the foundation funding amounts. As a result, poor districts tended to receive larger state aid and thereby fiscal equity was supposed to improve (Ohio Legislative Service Commission, 2011, pp. 26-27).

The PASS funding mechanisms were unique in that they incorporated extra measures to enhance fiscal equity. The PASS included an educational challenge factor (ECF), which was applied to 11 sub-factors of the foundation funding amounts, including all seven factors of the Instructional Services Support component (e.g., core teachers, special teachers, etc.). The ECF considered three factors: college attainment rate, poverty rate, and per pupil wealth, to further enhance fiscal equity across school districts. The ECF resulted in higher foundation funding amounts with relatively low college attainment rate, relatively high poverty rate, and relatively low property and income wealth in local school districts (Ohio Legislative Service Commission, 2011, pp. 8, 12-13).

The PASS was the culmination of adequacy-based policies in Ohio since FY 2002, but starkly differed from the state aid formulas prior to FY 2010 (refer to Table 3). Although it was repealed after FY 2011, a transitionary funding system, the Bridge Formula, was implemented for FY 2012 and FY 2013. The Bridge Formula applied the foundation amount used for the

PASS although it retained some components like a new foundation formula implemented since FY 2014, which was designed to be more wealth-neutralizing and similar to typical state aid formulas from the early 1970s to 1990, which aimed at fiscal equity (Ohio Education Department, 2010a; Ohio Education Department, 2013).

Data and Model

Data

Table 1 provides descriptive statistics of the variables used in this paper for about 607 local Ohio school districts from FY 2010 to FY 2019. All dollar values are presented in 2019 constant dollars, applying the State and Local Government Price Deflator. The main outcome of interest should be student test scores because adequacy-based school funding attempts to enhance students' educational achievement or outcome. *Performance_Index_Score* in Table 1, is Performance Index Score that measures proficiency of students' educational performance. *Performance_Index_Score* is the primary performance measure used for local Ohio school districts. *Performance_Index_Score* is constructed from various test scores across different subject areas for students in various grades. Ohio Revised Code Section 3302.01 (A) requires all subjects, including English Language Arts (ELA), math, and science, to be included for grades 3-8 when constructing *Performance_Index_Score*. For high school end-of-course tests, only the tests in ELA and math are included.

The level of educational achievement for each student for each state test is tallied into one of the seven ranges of proficiency: Advanced Plus, Advanced, Accelerated, Proficient, Basic, Limited, and Tests Not Taken. For each range, there is a state-set weight that is multiplied to the percentage of student scores that satisfy the proficiency hurdle for each range. The weighted sum of the percentages in the seven ranges generates Performance Index Score for each school district. By construction, 120 is regarded as a perfect score. *Performance_Index_Score* for FY 2020 is not available due to the COVID-19 pandemic, so this paper uses *Performance_Index_Score* up to FY 2019. Data for *Performance_Index_Score* come from various issues of *Ohio School Report Cards*. Table 1 shows that the mean of *Performance_Index_Score* is about 94.5, with standard deviation of about 9.5. The minimum *Performance_Index_Score* is about 52.1 and the maximum score is about 113. There are 6056 district-year observations. Data for all other variables come from a series of *District Profile Report*.

Percent_Disadvantaged is the percentage of economically disadvantaged students, which measures the percent of the total student population identified as disadvantaged. According to the series of *District Profile Report*, this variable was provided as the percent of students in poverty up to FY 2015, which measures the portion of a district's population that meets certain poverty conditions. Despite the variable name change, the series indicates that they are the same variables. About 42.3 percent of the student population is economically disadvantaged. *Percent_Disability* measures the percentage of students in school districts who are under a handicapping condition and need special attention. About 13.8 percent of the total student population falls in this category of student. Most studies introduced in Section 2 use these two variables reflecting student characteristics as primary independent variables for their regression models.

Teacher_Salary is the average salary of all FTE classroom teachers. The classroom teacher average salary is about $60626. *Median_Income* is the median income of the residents in school districts as reported by the Ohio Department of Taxation. Since the series of *District*

Profile Report uses property valuation on a tax year (TY) basis, *Median_Income* is also used on a TY basis. For instance, median income for TY 2015 is matched to FY 2016. The average median income across school districts is about $37896. *Formula_Aid* measures per pupil state aid to school districts. For fiscal years 2010 and 2011, state aid was distributed according to the formula in Ohio's PASS. For fiscal years 2012 and 2013, state aid amount was computed based on the Bridge Formula. Since FY 2014, state aid amount was set based on the Foundation Formula like typical foundation aid in other states, which intends to improve fiscal equity (Ohio Revised Code Sections, 3317.012, 3317.017, 3317.0217, and 3317.022). The average of per pupil state formula aid for the entire study period is about $4531.

Property_Valuation measures per pupil assessed property valuation that reflects the fiscal capacity of school districts because local property taxes, one of the major revenue sources for local school districts, are levied on assessed property valuation. The mean of *Property_Valuation* is about $163065.973. *Property_Valuation_In_2010* is an instrumental variable used for estimating regression models introduced in the next section. *Property_Valuation* of each school district for FY 2010 is adjusted only for the State and Local Government Price Deflator. For instance, if the price level increased by 5 percent from FY 2010 to FY 2011, then the value of *Property_Valuation_In_2010* for FY 2011 is equal to 105 percent of *Property_Valuation* in FY 2010. This adjustment is made for all years after FY 2010. As a result, *Property_Valuation_In_2010* reflects the change in the price level in property valuation, effectively filtering out any other potential endogenous effects reflected into property valuation (e.g., capitalization effects caused by student test scores in school districts). Although this variable is not the focus of causal inference, studies show strong capitalization effects from student test scores (Lafortune & Schönholzer, 2022). As a way around the endogeneity issue, therefore, *Property_Valuation* is instrumented with *Property_Valuation_In_2010*. The average of *Property_Valuation_In_2010* is about $179666.

Finally, *Treat* is constructed to answer the main research question in this paper, namely the distributional impacts of 'repealing' the PASS on Performance Index Score. First, average values of per pupil property valuation, *Property_Valuation*, for each school district are computed for ten years (i.e., FY 2010 – FY 2019). Second, *Treat* is equal to 1 if a certain school district's ten-year average value belongs to the bottom 25th percentile of the distribution of the average values. *Treat* is equal to 0 if the ten-year average value belongs to the upper 75 percent in the distribution. As explained in the next section, we can see the distributional impacts of repealing the PASS by interacting *Treat* with year.

Model: Difference-in-Differences (DiD)

De Witte and López-Torres (2017) conducted a thorough review of 223 journal articles on what factors affect educational outcomes, which were published between 1977 and 2015. They defined educational outcomes as a function of students' characteristics, family-related factors, features of educational institutions, community/environmental factors, etc. Handel and Hanushek (2023) reported similar factors affecting educational outcomes. The variables in Table 1 approximately cover students' characteristics, features of educational institutions, and community/environmental factors that are expected to affect Performance Index Score.

For econometric estimation of the distributional impacts of repealing PASS, this paper applies a Difference-in-Differences (DiD) estimation based on Two-Way Fixed Effects (TWFE) approaches, which has recently become more popularized (Roth, Sant'Anna, Bilinski, & Poe, 2023; Callaway & Sant'Anna, 2021; Liu, Wang, & Yiqing Xu, Forthcoming). If the assumptions of parallel trends and no anticipatory effects are satisfied, then TWFE models with an appropriate treatment indicator can estimate treatment effects under a canonical two-group, two-period DiD setup. We can easily extend the canonical setup to a dynamic TWFE DiD model as the following (Roth, Sant'Anna, Bilinski, & Poe, 2023):

$$Y_{it} = \alpha_i + \phi_t + \sum_{\substack{r \neq 2013 \\ 2010 \leq r \leq 2019}} Treat * 1[t = r]\beta_r + \sum_{p=1}^{k} X_p * [t > 2013]\gamma_p + \varepsilon_{it} \quad (1)$$

, where Y is *Performance_Index_Score*, i denotes individual school district, t denotes year, α_i measures unit-fixed effects, ϕ_t taps time-fixed effects, *Treat* is an indicator that a school district belongs to the bottom 25 percent in the distribution of per pupil property valuation, X is a vector of k independent variables listed in Table 1 except for *Property_Value_In_2010* that is used as an instrument for model estimation, and ε_{it} is an idiosyncratic error associated with school district i in year t. The function '1[.]' is an indicator that returns 1 if the condition inside the brackets '[.]' is satisfied and 0 if it is not.

The key part in Equation (1) is the third component in the right-hand side of the equation. *Treat* is interacted with a dummy variable for each year except for 2013 that is used as an intercept. In short, there are nine dummy variables that are coded 1 for treatment units for each year separately and an intercept. Although the PASS was repealed at the end of FY 2011, the Bridge Formula applied the base foundation amount in the PASS as its starting point for aid calculation until FY 2013. Thus, it is reasonable to assume that the PASS is finally phased out at the end of FY 2013. As Roth, Sant'Anna, Bilinski, & Poe (2023) suggest, we can augment the TWFE specification with controls for a time-by-covariate interaction as in $X_p * [t > 2013]$, for which we need an additional homogeneity assumption. All the variables starting with "*PT_*," which stands for post treatment, are time-by-covariate interactions variables. In short, the interaction variables are 0 for the years before FY 2014 and the same as the covariates, X_p, after FY 2013.If X_p causes heterogeneous treatment effects (e.g., treatment effects vary by student characteristics, for instance), however, the homogeneity assumption is likely to be violated. One way around the potential violation of the assumption is utilizing various covariate balancing techniques to equalize the values of chosen covariates as tightly as possible between control and treatment units.

This paper further applied various balancing approaches such as Entropy Balancing (Hainmueller, 2012), Coarsened Exact Matching (Iacus, King, & Porro, 2012), and Overlap Weighting (Zeng, Li, Wang, & Li, 2021). These methods are proposed to outperform Propensity Score Weighting or Matching that often generates highly variable weights and as a result, may introduce bias in weight estimates. However, these methods did not achieve covariate balancing at a desirable level. Instead, this paper applied Stable Balancing Weights (SBW) (Zubizarreta, 2015; Chattopadhyay, Hase, & Zubizarreta, 2020; Resa & Zubizarreta, 2020), which achieved covariate balancing up to a user-specified level. Since SBW was originally proposed to impute missing cases (i.e., missing cases were defined as treated units), we need to adapt the original SBW optimization schemes to the data set in this paper:[1]

$$\underset{w}{minimize} \sum_{i:Z_i=0}(w_i - \overline{w_c})^2 \quad (2)$$

$$\text{subject to } \left|\sum_{i:Z_i=0} w_i X_i - \frac{1}{n_t}\sum_{i:Z_i=1} X_{ip}\right| \leq \delta_p, p = 1, \dots, k \quad (3)$$

$$\sum_{i:Z_i=0} w_i = 1 \quad (4)$$

$$w_i \geq 0, i: Z_i = 0 \quad (5)$$

, where w_i is SBW for control units, $\overline{w_c}$ is the average of the control weights, $i: Z_i = 0$ ($i: Z_i = 1$) denotes control status (treatment status), and n_t is the number of treatment units. Equation (3) subjects the absolute difference between the weighted average of X_i for control units and the average value of X_i for treatment units to a user-specified scalar, δ, for all k covariates. In this paper, δ is set at 0.001 such that the absolute difference should be less than 0.001. Equation (4) subjects the sum of weights to one to minimize the coefficient of variation of the weights. Equation (5) is a usual non-negativity constraint. Equation (2) minimizes deviations of the weights from their mean value. Equation (3) indicates that this restriction weights control units to represent treatment units, which by construction enables computing Average Treatment Effects on the Treated (ATT). In this paper, SBW is obtained for each year separately and then, the combined SBWs for all years are used for running survey-design-based weighted least square regressions (Hainmueller, 2012; Hainmueller & Xu, 2013).

Findings and Discussions

Table 2 reports the estimation result from the TWFE DiD model. The analysis of time-by-covariate interactions reveals deviations in their effects compared to the effects observed at pre-treatment covariate levels. *PT_Property_Valuation* positively affects *Performance_Index_Score* but increased *Performance_Index_Score* might be capitalized into property valuation. To address this endogeneity, an interaction variable between *Property_Valuation_In_2010* and post-2013 dummy is used as an instrument for *PT_Property_Valuation*. All the test statistics indicate that the instrument is valid. In particular, the Kleibergen-Paap test statistic for weak instrument is 1,740.2 ($p < 2.2e-16$), which is much larger than the threshold value of 10 (Kleibergen & Paap, 2006; Baum, Schaffer, & Stillman, 2007; Staiger & Stock, 1997), 104.67 (Lee, McCrary, & Moreira, 2022), or 50 (Keane & Neal, 2024), for one endogenous with one instrument. The coefficients of *PT_Percent_Disadvantaged* and *PT_Percent_Disability* indicate that these student characteristics exert further negative impacts on *Performance_Index_Score* during post-treatment years. *Teacher_Salary* positively affects *Performance_Index_Score* during post-treatment years but its impact is statistically insignificant. The remaining two variables, *PT_Median_Income* and *PT_Formula_Aid*, exert further positive post-treatment impacts on *Performance_Index_Score* but their impacts are miniscule.

Except for year 2013 that was used as the base year, there are nine interaction variables between *Treat* and year for all other years. These variables reveal dynamic impacts of repealing the PASS on the treatment units (i.e., the 25th percentile in the distribution of per pupil property valuation). Testing the assumption of parallel trends for control and treatment units requires more elaborate statistical assumptions and tests. Instead, researchers test pre-treatment trends or pre-trends as an alternative to testing parallel trends (Roth, Sant'Anna, Bilinski, & Poe, 2023). Table 2 indicates that treatment units do not show pre-trends distinguishable from control units in terms of *Performance_Index_Score*: the coefficients of '*Treat * year*' before FY 2013 are all statistically indistinguishable from zero. Figure 1 visualizes no pre-trends as well.

Most importantly, the coefficients of '*Treat * year*' after 2013 provide clues for answering the research question in this paper: distributional impacts of repealing the PASS on *Performance_Index_Score*. Surprisingly, repealing the PASS resulted in increases in *Performance_Index_Score* for the treated units, the bottom 25 percent in the distribution of property valuation for years 2014 and 2015. Since 2016, the poorest school districts suffered from drops in *Performance_Index_Score*. While the poorest school districts experienced unexpected increases in *Performance_Index_Score* for two years, their student performance declined after 2015. This is possibly attributable to the elimination of ECF formulas attached to the PASS. Dropping the formulas that protected fiscal equity also dropped student performance in the poorest school districts in the longer run. Figure 1 also visualizes these patterns. However, there is one caveat: the negative impacts observed after 2015 were not statistically significant upon a rigorous robustness check, leaving the positive impacts in 2014 and 2015 as the primary significant findings.

The increase in *Performance_Index_Score* by about 2.25 to 2.28 points after the repeal of the PASS is not negligible. According to recent studies (Jackson & Claudia Persico, 2023 a; Jackson & Mackevicius, 2024; Handel & Hanushek, 2023), a $1000 increase in per pupil spending boosts student test scores by about 4.4 to 4.7 percent of a standard deviation. According to Table 1, one standard deviation of *Performance_Index_Score* is 9.431 points. Therefore, the increase of 2.25 to 2.8 points suggests that student test scores increased by approximately 23.9 to 24.2 percent of a standard deviation. This impact amounts to what an approximately $5286 increase in per pupil spending can achieve.

Robustness Check

The primary findings for years 2014 and 2015 stayed almost unchanged even after controlling for potentially confounding factors.

Confounding Impacts of Federal Aid

The No Child Left Behind Act (NCLB) of 2001 imposed top-down federal intervention on local educational agencies with performance reporting and outcome-based assessments. It tied the federal Title I funding to student achievement outcomes in math and English language arts. States may choose their own tests but were required to raise performance to a national target of 100 % proficiency by 2014. School districts and schools that failed to make the needed progress was supposed to be subject to improvement, corrective actions, or restructuring measures (van der Klaauw, 2008; Egalite, Fusarelli, & Fusarelli, 2017; Husband & Hunt, 2015). However, the unachievable performance goal by 2014 and lack of local discretion in the NCLB invited numerous critiques. As a result, the Every Student Succeeds Act (ESSA) of 2015 substantially loosened the tight federal control over Title I funded programs. States were allowed to develop their own pedagogical strategies for low-performing schools (e.g., typically the bottom 5 percent in the distribution of student performance) (Egalite, Fusarelli, & Fusarelli, 2017).

The Ohio Department of Education submitted its ESSA plan to the U. S. Department of Education in 2017 and the U. S. Department of Education approved the plan in 2018. The Ohio Department of Education submitted a revised plan in 2022, and the U. S. Department of Education approved it in 2023.[2] Therefore, Ohio's ESSA plan does not overlap with the study period in this paper. However, many states applied for waivers from NCLB interventions regarding student performance even before ESSA. Ohio is one of the states that received the NCLB waivers in 2012.[3] If the schools received the NCLB waivers with state's special educational programs, then the school districts, to which the schools belong, might have benefited from the special programs. Since these schools are likely to be in poorer school districts, *Treat* in this paper might be confounded by the special programs.

While obtaining school district identification numbers of the schools with the NCLB waiver is the best strategy to filter out the differential impact from the potential programs, it was difficult to retrieve the identification numbers.[4] Bonilla and Dee (2017, footnote 5) indicate that states receiving NCLB waivers were required to identify and have the bottom 5 percent schools in the distribution of student performance implement federally prescribed programs. Of course, the latter programs might include states' special educational programs. To control for this potentially confounding impact, Equation (1) was estimated again with an interaction variable, *Low_Performance_Treat*, which is constructed as: $Treat * [t > 2013] * [perf_i \leq perf_{5^{th}}]$, where $perf_i$ is the ten-year average of *Performance_Index_Score* for school district *i* and $perf_{5^{th}}$ is the bottom 5th percentile in the distribution of ten-year average

Performance_Index_Score values for all school districts. The coefficient of *Low_Performance_Treat* was -1.825 ($p < 0.001$) but the coefficients of the interaction variable, '*Treat * year*,' were almost identical to those in Table 2 for all years. This finding implies that state's potential programs might not confound the treatment effects.

Confounding Impacts of Other Unknown Interventions

A related issue is that some unknown policy interventions might still confound the impacts of the PASS repeal. Scholars have alerted us about the potential confounding (Jackson & Persico, 2023a, 2023 b; McGee, 2023). One way around this possible confounding is testing an interaction variable, *Treat_Aid*, as *Treat * Formula_Aid*, in Equation (1) instead of *Treat*. The interaction variable directly analyzes the impacts of specific per pupil dollar amounts of state aid money. The DiD estimation result with the interaction variable is virtually the same as that in Table 2, thus ruling out the unknown but potential confounding effect as well.

Confounding Impacts of Imperfect Balancing

As noted earlier, time-by-covariate interactions might introduce heterogeneous treatment effects. One way around this potential bias in estimating treatment effects is applying covariate balancing techniques. In fact, balancing covariates for all years is intuitively identical to securing the parallel trends for both pre-treatment and post-treatment years as well (Callaway & Sant'Anna, 2021; Roth, Sant'Anna, Bilinski, & Poe, 2023).

Table 4 shows the SBW-weighted regression result. The weighted regression included *Low_Performance_Treat* as well.[5] *pred_val*, which is the predicted value of the regression of *PT_Property_Valuation* on the interaction variable between *Property_Valuation_In_2010* and post-2013 dummy, was used instead of *PT_Property_Valuation* to make the result consistent with that in Table 2. Table 4 confirms again that repealing the PASS resulted in increases in

Performance_Index_Score for the treated units for years 2014 and 2015, with the magnitude of the increases almost unchanged. However, the impacts of repealing the PASS differed slightly from those in Table 2. *Performance_Index_Score* dropped for treated units only for 2016 and the drops after 2016 were statistically insignificant. Overall, repealing the PASS surprisingly benefited bottom 25 percent school districts in the distribution of property valuation immediately after the PASS was finally terminated at the close of the transition period, 2013. Despite the one-year drop in *Performance_Index_Score* due possibly to the elimination of ECF formulas, the poorest school districts were not damaged further after 2016.

Since covariate balancing might still fail to address the potential heterogeneous impacts that time-by-covariate interaction variables might generate, it is a good idea to run quantile regressions along a decile of *Performance_Index_Score* to see whether the variables exert differential impacts on *Performance_Index_Score*. Only the coefficients of *PT_Percent_Disadvantaged* and *PT_Percent_Disability* for the ninth and tenth deciles (i.e., the upper 20 % in the distribution of *Performance_Index_Score*) were somewhat different from those for other quantiles. In addition, the coefficient of *PT_Percent_Disadvantaged* consistently increased from the lowest quantile to the tenth decile regressions. Thus, a new SBW-weighted regression model excluded observations with $perf_i \geq perf_{80^{th}}$ and included an additional interaction variable, *PT_Percent_Disadvantaged * Treat*, to filter out the potential heterogeneous impacts noted above. The impacts of repealing the PASS were 2.94 and 1.88 (both statistically significant) for FY 2014 and FY 2015, which were almost identical to those in Table 4. The negative impacts for FY 2016 as well as the years after FY 2016 were now statistically insignificant. The results are almost identical to those in Table 2. The only difference is that now even the drop in *Performance_Index_Score* since FY 2016 is not statistically significant, leaving the unexpected increase for FY 2014 and FY 2015 only.

Confounding Delayed Impacts

It's likely that students in less affluent districts were only beginning to reap the benefits of increased funding when it was discontinued. As a consequence, their test scores improved in 2014 and 2015, even after the program ended. Essentially, they had enjoyed 3 to 4 years of enhanced services, but the positive effects on their education took time to manifest. It required several years of better conditions before the improvements became evident. This might have led to an uptick in their performance, which subsequently declined after a few years without sufficient funding.

As long as the lagged impact on students' learning followed similar parallel trends between the treatment and control groups, DiD models are expected to account for these delayed effects. However, there is still a possibility that students in poorer districts might experience a different type of learning curve. To address this, the amounts of PASS funding in 2010 and 2011 only for the poorer districts were added for the years 2014 and 2015 in Equation (1). These lagged PASS funding amounts did not achieve statistical significance. When Bridge funding from 2012 and 2013 for the poorer districts was further added for 2014 and 2015, the Bridge funding had some statistically significant impacts on student test scores, but the overall patterns remained largely unchanged.

Exploring Unexpected Findings

With these unexpected findings, one interesting question is lingering. Why does repealing adequacy-based state aid formula enhance student performance in the poorest districts while the literature reported that the impacts of adequacy-based spending on student performance were more pronounced in the districts and as a result, one can expect that its repeal might damage the poorest districts? As noted earlier, the PASS was a state legislation with strict categorizations of funding amounts for each of the PASS items. Jackson (2018) indicates that school funding with spending restrictions such as Title I fund tends to show weaker impacts on student performance, which might be attributable to the lack of discretion on the part of educational agencies.

Lafortune, Rothstein, and Schanzenbach (2018) reported that the increased school spending from school finance reforms (SFRs) boosted student performance. More interestingly, poorer school districts used almost half of the spending on capital spending. As introduced above, the PASS distributed disproportionately larger amounts of state aid to instructional spending. The PASS repeal might have enabled the poorer districts to use state aid money for the programs they deemed most effective for student learning, for instance, capital projects. However, another round of detailed analysis identifies changes in spending patterns in the poorer school districts (i.e., treatment districts), which tell a story different from that in Lafortune, Rothstein, and Schanzenbach (2018).

Figure 2 presents the changes in spending patterns along twelve ratio variables. Data for the first six ratio variables come from a series of *District Profile Report*, which measure the share of each variable out of total expenditures. *ratio_admin* is the share of administration expenditures, *ratio_building_oper* is the share of building operation expenditures, *ratio_inst* is the share of instructional expenditures, *ratio_support* is the share of pupil support expenditures, and *ratio_staff_support* is the share of staff support expenditures. *ratio_aid* is state formula aid divided by total revenues. Since the series of *District Profile Report* does not provide more detailed data on capital spending, additional data are collected from the *Common Core of Data* from the National Center for Education Statistics. The six additional capital spending variables are also ratio variables, which measure the share of each variable out of total expenditures. *ratio_tot_cap* is the share of total capital expenditures, *ratio_construction* is the share of capital outlay for construction, *ratio_land_exist* is the share of capital outlay for land and existing structures, *ratio_inst_equip* is the share of capital outlay for instructional equipment, *ratio_other_equip* is the share of capital outlay for other equipment, and *ratio_nonspec_equip* is the share of capital outlay for non-specified equipment.

Each of the above twelve ratio variables is used as a dependent variable in a DiD model that has the same model specification as Equation (1). The only difference is that *PT_Property_Valuation* is not instrumented. Figure 2 suggests that changes in spending patterns for four ratio variables provide some useful clues for answering the lingering question. *ratio_support* is 0 for FY 2013 (e.g., intercept) and statistically significant and negative for all other years. For FY 2014, the 95 percent confidence interval almost covers 0. If we use *Treat_Aid* (= *Treat* * *Formula*_Aid) for DiD estimation, the 95 percent confidence interval for *ratio_support* covers 0 for FY 2014 (see Figure 3). In sum, the poorer school districts spent on pupil support expenditures as much as their wealthier counterparts spent during FY 2013 and FY 2014. A series of *District Profile Report* indicates that pupil support service includes student counseling, psychological services, health services, social work services, etc. After the PASS repeal, the poorer districts spent relatively more or at least as much as their wealthier counterparts did on student well-being for two years. *ratio_staff_support* is statistically significant and positive for FY 2010, FY 2011, and FY 2012. For all other years, it is not distinguishable from 0. The poorer districts seem to have decreased their spending on staff support services beginning from FY 2013 (during one of the transition years when the PASS was being phased out). *ratio_inst_equip* and *ratio_other_equip* are statistically significant and positive for FY 2011 when the PASS was still in effect and indistinguishable from 0 for all other years. The poorer districts started decreasing their spending on these spending categories starting from FY 2012.

Despite facing funding cuts, the poorer school districts redirected spending towards student support services like counseling and health services, while reducing investment in staff support and equipment. This shift helped mitigate the negative impact of funding cuts and might have contributed to unexpected gains in student test scores, emphasizing the importance of prioritizing student well-being.

Conclusions

During the so-called adequacy of education era, many state governments have endeavored to equalize not only fiscal resources but also educational outcomes or student performance. Numerous studies have empirically shown that adequacy-based educational funding significantly improved student performance, especially in impoverished school districts. Ohio was one of the states that had implemented its own version of adequacy-based state aid, called the PAthway to Student Success (PASS) in FY 2010. However, the PASS was repealed at the close of FY 2011. Since no studies have yet examined the impact of repealing the PASS on student performance, this paper attempts to fill in the gap in the literature. Unlike our expectations, repealing the PASS improved student performance in the poorer school districts in Ohio. The unexpected improvement in student performance is ascribed to the increased adaptability gained by removing stringent limitations on aid money, allowing for more focused resource allocation to areas of greatest need. The decrease in fiscal equity (e.g., the elimination of ECF formulas) did lessen the initial positive effect on student performance in the economically disadvantaged districts over time but it is important to note that the long-term impact did not lead to a significant drop in student performance.

Poorer school districts defied expectations by achieving unexpected test score gains despite facing cuts to adequacy-based funding that boosted student performance in poorer districts according to the literature. This surprising outcome can be attributed to shifts in local spending patterns. In a bold move, these districts prioritized student well-being by increasing investments in crucial support services like counseling, psychological services, and health programs. This came at the expense of decreased spending on staff support and equipment. The increased focus on student support services might have mitigated the negative effects of funding cuts, potentially leading to the observed gains in test scores. This finding highlights the potential benefits of prioritizing student well-being, even in resource-constrained environments. These results underscore the crucial role that local discretion plays in resource allocation. By making tailored spending decisions, local school districts can address specific needs and priorities within their communities. This approach demonstrates that even in the face of significant funding challenges, carefully targeted investments can significantly enhance educational outcomes.

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Endnotes

[1] The independent variables in Equation (1) failed to achieve desirable balance. Thus, a different set of covariates was used. *Percent_Disadvantaged* and *Percent_Disability* were the only variables from Equation (1). Other variables are: % of Asian students, % of black students, % of Hispanic students, % of white students, % of students with limited English proficiency, % of teachers with 4 years of experience, and % of teachers with more than 10 years of experience. Regression models may control for variables other than those used for covariate balancing (Hainmueller 2012).

[2] https://education.ohio.gov/Topics/Every-Student-Succeeds-Act-ESSA [accessed October 10, 2023]

[3] https://www.wfmj.com/story/18658390/ohio-receives-waiver-from-no-child-left-behind-law# [accessed October 13, 2023]

[4] The responses of the Ohio Department of Education to this author's data request do not provide the identification numbers but indicate that the bottom five percent districts are likely targets of the new interventions.

[5] When *Low_Performance_Treat* was not included, the result was almost identical to that in Table 4.

Table 1: Descriptive Statistics

Variable	n	Mean	S.D.	Min	Max
Performance_Index_Score	6056	94.491	9.431	52.114	113.013
Percent_Disadvantaged	6056	0.423	0.219	0.000	1.000
Percent_Disability	6056	0.138	0.033	0.042	0.279
Teacher_Salary	6056	60626.254	9341.353	0.000	130720.018
Median_Income	6056	37895.714	8927.607	13744.000	86816.053
Formula_Aid	6056	4531.199	2215.702	-197.356	14773.384
Property_Valuation	6056	163065.973	75223.060	44932.410	1062325.240
Property_Valuation_In_2010	6056	179665.646	86973.866	54680.779	1064264.684
Treat	6056	0.250	0.433	0.000	1.000

Table 2: Regression Results for the Bottom 25th Percentile as Treated Units

Dependent Var.:	*Performance_Index_Score*
PT_Property_Valuation	2.2e-6* (1.11e-6)
PT_Percent_Disadvantaged	-6.888*** (0.5181)
PT_Percent_Disability	-14.32** (2.175)
PT_Teacher_Salary	6.26e-7 (6.59e-6)
PT_Median_Income	3.56e-5** (1.12e-5)
PT_Formula_Aid	0.0001*** (3.93e-5)
*Treat * year = 2010*	-0.3663 (0.2905)
*Treat * year = 2011*	0.0028 (0.2698)
*Treat * year = 2012*	-0.0117 (0.2560)
*Treat * year = 2014*	2.247*** (0.2861)
*Treat * year = 2015*	2.277*** (0.2973)
*Treat * year = 2016*	-2.040*** (0.3570)
*Treat * year = 2017*	-1.428*** (0.3403)
*Treat * year = 2018*	-1.644*** (0.3545)
*Treat * year = 2019*	-1.374*** (0.3580)
Fixed-Effects:	
irn	Yes
year	Yes
S.E. type	Heteroskedasticity robust
Observations	6,056
R^2	0.94673
Within R^2	0.25738
Standard errors are in parentheses. Kleibergen-Paap: stat = 1,740.2, p < 2.2e-16, on 1 DoF. Cragg-Donald: 10,849.5 Wu-Hausman: stat = 19.7, p = 9.093e-6, on 1 and 5,424 DoF. F-test (1st stage), *PT_Property_Valuation*: stat = 9,723.9, p < 2.2e-16, on 1 and 5,425 DoF.	
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (fixed effects are omitted)	

Table 3: Summary of Formula Changes in Ohio School Aid

Foundation Program between FY 2002 and FY 2005
• Base Cost Per Pupil = {Cost of Doing Business (CODB) Factor * Base Cost Formula Amount} - (0.023 * District Recognized Property Valuation Per Pupil} • Where, Base Cost Formula Amount = cost of an adequate education per pupil in school districts that met 20 of 27 performance indicators, established in 2001 based on 1999 data, for FY 2002, for instance • Base Cost Formula based on adequate education, first applied to FY 1998 • Among several adjustments, Parity Aid Per Pupil = 9.5 mills * District Recognized Property Valuation Per Pupil * |District Wealth Per Pupil - Average Wealth Per Pupil of the 10^{th} to 30^{th} Districts with the highest wealth per pupil| • Where, Wealth Per Pupil = {(2/3) * District Recognized Property Valuation + (1/3) * Average Resident Personal Income}/ Formula Average Daily Membership (ADM) • Therefore, wealthier districts tend to receive relatively smaller state funding and the state-set foundation amount reflects the so-called adequacy of education clause.
Foundation Program between FY 2006 and FY 2010
• Base Cost Per Pupil is now calculated based on the cost of building blocks: classroom teachers, other personnel support, and non-personnel support. • Then, Base Funding Supplement Per Pupil is set for: large group intervention, professional development, data-based decision making, and professional development regarding data-based decision making. • Amounts of Parity Aid slightly decreased. • Overall, wealthier districts tend to receive relatively smaller state funding and the adequacy of education clause is more strongly embedded in the state funding formula.
PAthway to Student Success (PASS) Funding for FY 2010 and FY 2011
• State-defined Education Cost for: Instructional Service Support, Additional Services Support, Administrative Services Support, Operations and Maintenance Support, Gifted Education and Enrichment Support, Technology Resources Support, Professional Development, and Instructional Materials • Cost Estimation for Core Teachers for Instructional Service Support, for instance: For grades K through 3, Number of core teachers in each grade level = (ADM in the grade level) / 19; For grades 4 through 12, Number of core teachers in each grade level = (ADM in the grade level) / 25 • Then, costs for each of the above categories are assigned based on the Evidence-Based Model (EBM) approach, which previous empirical research findings provides. • Parity Aid in previous formulas stay as the Educational Challenge Factor (ECF), which is based on three measures: college attainment rate, poverty rate, and wealth per pupil in school districts. • Overall, wealthier districts tend to receive relatively smaller state funding but the state-set foundation amount strictly exemplifies adequacy-based funding via the EBM formulas.
Bridge Formula for Ohio State Foundation Funding for FY 2012 and FY 2013
• Foundation Funding Per Pupil = FY 2011 Foundation Funding Per Pupil - District Adjustment Amount Per Pupil

• Where, District Adjustment Amount Per Pupil = District Property Valuation Index * Statewide Per Pupil Adjustment Amount • Where, District Property Valuation Index is constructed from (District Property Valuation Per Pupil / Statewide Median Property Valuation Per Pupil) • Therefore, wealthier districts tend to receive relatively smaller state funding.
FY 2014 Foundation Formula until FY 2023
• There are eleven state grant programs that include foundation funding components. For each of them, there is one common factor, called State Share Index. • State Share Index = 0.9 if Wealth Index =< 0.35 ; else {0.4 * [(0.9-Wealth Index) / 0.55]} + 0.5 if 0.35 < Wealth Index =< 0.9; else State Share Index = {0.45 * [(1.8 - Wealth Index) / 0.9]} + 0.05 if 0.9 < Wealth Index =< 1.8; else 0.05 if Wealth Index => 1.8 • Where, Wealth Index = (2/3) * Valuation Index + (1/3) * Income Index if Valuation Index > Income Index; else Wealth Index = Valuation Index • Where, Income Index = District Median Income / State Median of the Medians and Valuation Index is similar to the Valuation Index for the Bridge Formula. • Then state fund per pupil = state-set lump sum foundation amount * State Share Index; wealthier districts tend to receive relatively smaller state funding. • The above formulas stay almost similar until FY 2021 except that the quotients used for State Share Index and Wealth Index have slightly changed. For FY 2022 and FY 2023, the two indices have somewhat changed but the main approach remains similar. • Parity Aid remains almost unchanged until FY 2013. Between FY 2014 and FY 2021, the quotients used for Wealth Per Pupil have slightly changed. For FY 2022 and FY 2023, Parity Aid formulas have somewhat changed.

Sources: various issues of *School Funding Complete Resource* published by the Ohio Legislative Service Commission, Ohio Revised Code Section 3317.012 for Base Cost for Adequate Education (as amended between CY 1998 and CY 2012), Ohio Revised Code Section 3317.0217 for Parity Aid (as amended between CY 2001 and CY 2021), Ohio Revised Code Section 3317.022 for Core Foundation Program (as amended between CY 1996 and CY 2021), Ohio Revised Code Section 3317.017 for State Share Index (as amended between CY 2005 and CY 2021), and Yazback (2007)

Table 4: Weighted Regression Results for the Bottom 25th Percentile as Treated Units

SBW-weighted regression				
variable	Estimate	Std. Error	t value	Pr(>|t|)
pred_val	0	0	1.087	0.277
PT_Percent_Disadvantaged	-6.219	0.9	-6.909	0***
PT_Percent_Disability	-15.647	3.449	-4.537	0***
PT_Teacher_Salary	0	0	-0.518	0.604
PT_Median_Income	0	0	1.093	0.274
PT_Formula_Aid	0	0	0.158	0.875
Low_Performance_Treat	-1.117	0.789	-1.416	0.157
Year_Treat2010	-0.083	0.432	-0.192	0.847
Year_Treat2011	0.498	0.443	1.125	0.261
Year_Treat2012	-0.158	0.424	-0.371	0.71
Year_Treat2014	2.829	0.48	5.889	0***
Year_Treat2015	1.969	0.464	4.242	0***
Year_Treat2016	-2.095	0.636	-3.293	0.001**
Year_Treat2017	-0.718	0.557	-1.288	0.198
Year_Treat2018	-0.688	0.53	-1.3	0.194
Year_Treat2019	-0.104	0.605	-0.173	0.863
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 (Fixed effects are omitted.)				

Figure 1: Treatment Effects - Bottom 25th Percentile

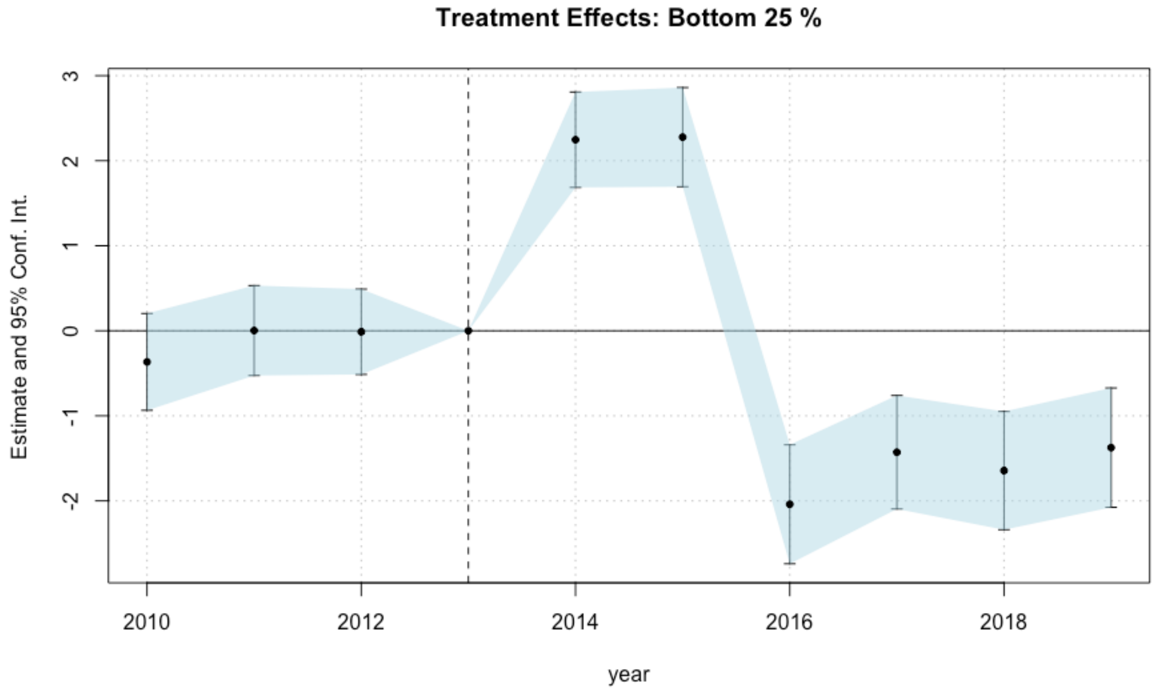
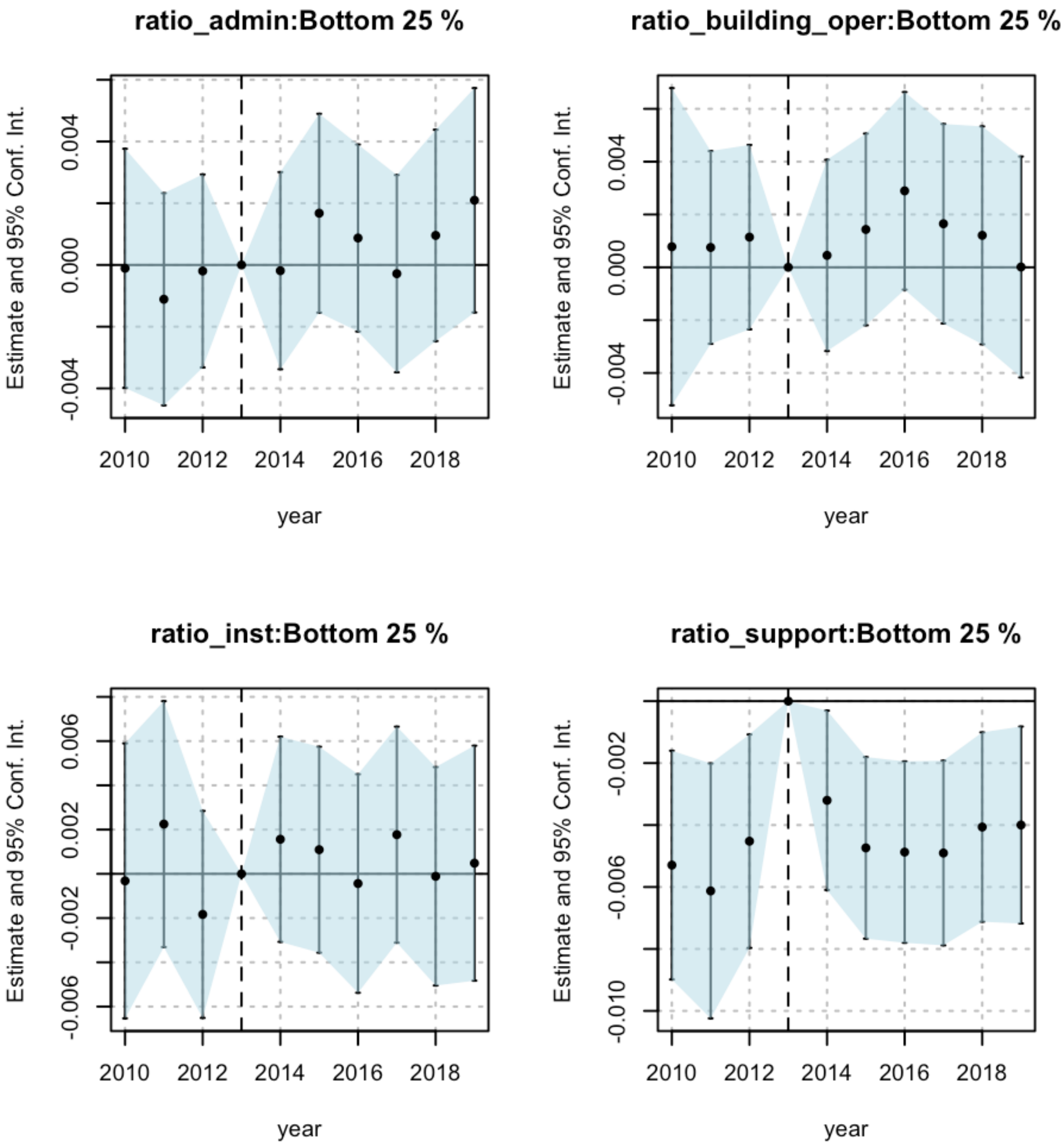
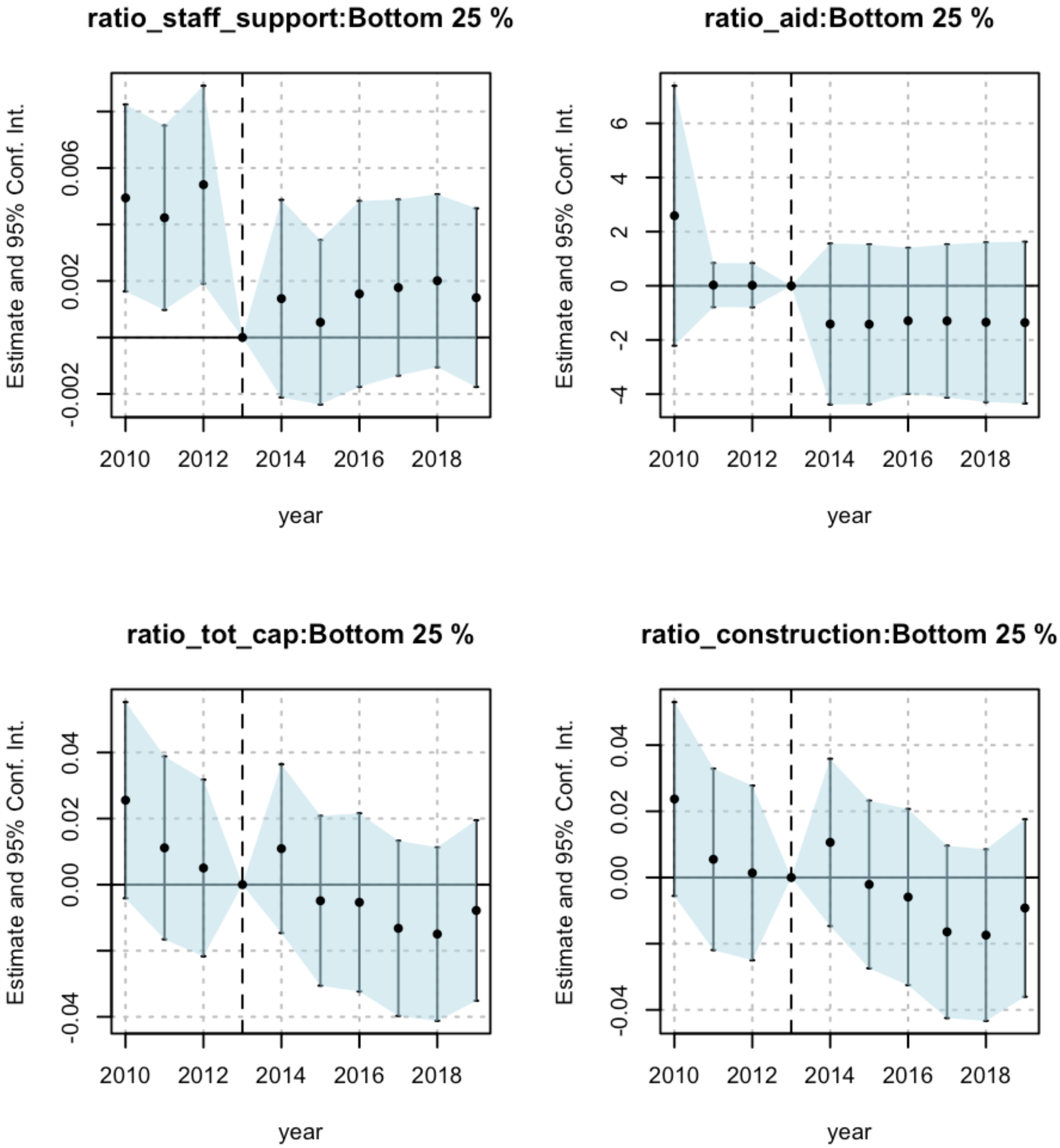


Figure 2: Changes in Spending Patterns - Bottom 25th Percentile




ratio_staff_support:Bottom 25 %
ratio_aid:Bottom 25 %
ratio_tot_cap:Bottom 25 %
ratio_construction:Bottom 25 %
Estimate and 95% Conf. Int.
year
2010
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2014
2016
2018
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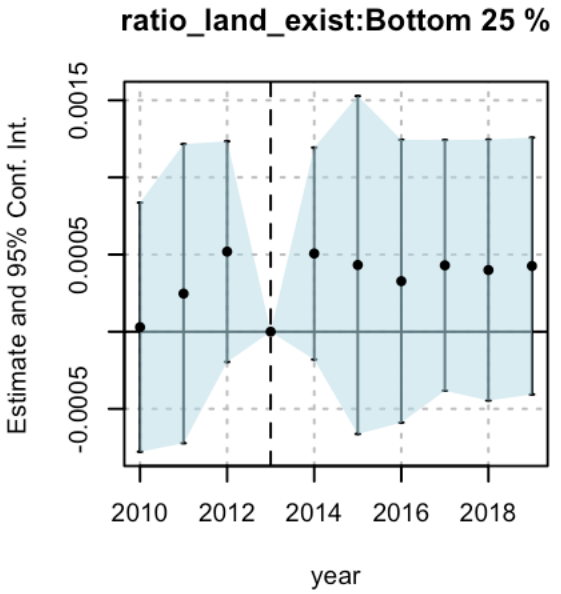
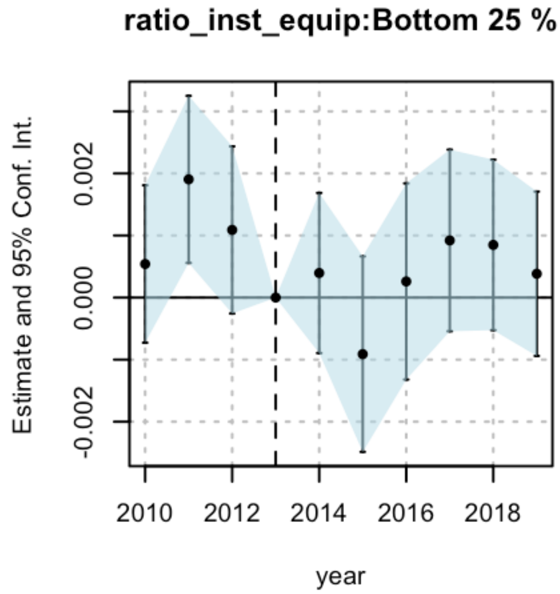
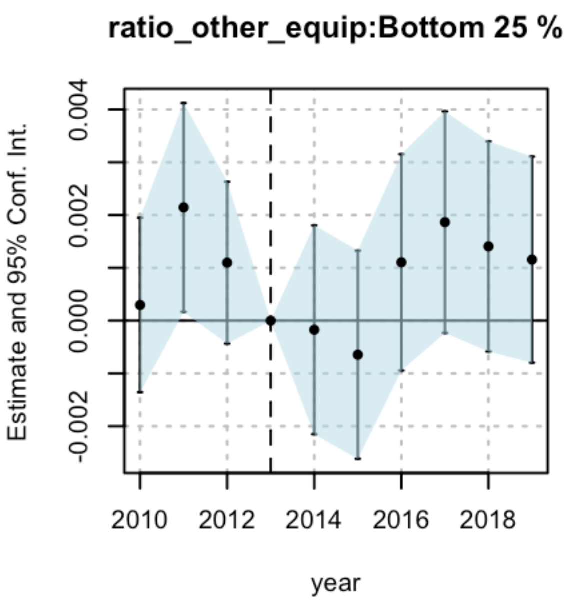
0.02
0.04


ratio_land_exist:Bottom 25 %
Estimate and 95% Conf. Int.
0.0015
0.0005
-0.0005
2010
2012
2014
2016
2018
year


ratio_inst_equip:Bottom 25 %
Estimate and 95% Conf. Int.
0.002
0.000
-0.002
2010
2012
2014
2016
2018
year


ratio_other_equip:Bottom 25 %
Estimate and 95% Conf. Int.
0.004
0.002
0.000
-0.002
2010
2012
2014
2016
2018
year

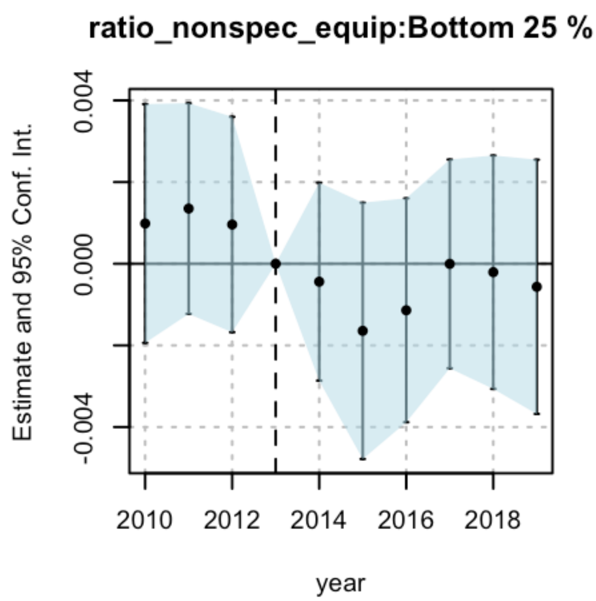

ratio_nonspec_equip:Bottom 25 %
Estimate and 95% Conf. Int.
0.004
0.000
-0.004
2010
2012
2014
2016
2018
year

Figure 3: Changes in Spending for Student Support - Bottom 25th Percentile