Student Performance, Fiscal Equity, and Outcome Equity: Assessing Ohio's PASS

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(Abstract) Since 1990, many states have pursued adequacy-based educational strategies, with the Evidence-Based Model (EBM) being one example. Ohio legislated EBM strategies into Ohio's PAthway to Student Success (PASS) during FY 2010 and FY 2011. This paper investigates how *repealing* the short-lived OH PASS affects student performance, fiscal equity, and outcome equity across local Ohio school districts between FY 2012 and FY 2019. The empirical findings in this paper reveal that repealing OH PASS tends to detract from student performance. In addition, there is a tradeoff between fiscal equity and outcome equity. Repealing OH PASS deteriorates fiscal equity but unexpectedly improves outcome equity.

Keywords: adequacy-based school funding, outcome equity, evidence-based model, Entropy Balancing
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1 Introduction

Between the early 1970s and 1990, many state governments attempted to equalize fiscal resources needed for K-12 public education systems. In particular, they utilized state aid to equalize school funding across local school districts by distributing disproportionately larger aid amounts to poor school districts. This era is largely defined as the era of fiscal neutrality or equity. The Kentucky Education Reform Act (KERA) of 1990 is a landmark legislation in that it has shifted the focus of school finance systems from fiscal equity to outcome equity. What should be equalized is not just fiscal resources but actual educational attainment of each student in public school systems. The period since 1990 is known as the Adequacy of Education era (Candelaria and Shores 2019, Jackson, Johnson and Persico 2016).

The adequacy era features the enhanced responsibility of state governments in guaranteeing that public education programs should be able to prepare students to meet state-set performance standards. Several methods have been proposed to initiate adequacy-based programs and strategies. The Evidence-Based Model (EBM) approach is one of those adequacy-based programs.

The EBM approach identifies and applies school-based programs and educational strategies, which previous research has empirically shown to improve student learning. EBM also incorporates the recommendations from state policy makers and educational leaders into its specific program details (Odden, Picus and Goetz 2010).

According to Candelaria and Shores (2019), thirteen states have adopted adequacy-based education programs since 1990. Ohio is one of the thirteen states. In a series of rulings in the *DeRolph* cases (1997, 2000, 2001, and 2002), the Ohio Supreme Court opined that the existing public education system was unconstitutional in that the system failed to provide adequate levels of education to students (Johnson and Vesely 2017, Simon 2015, Obhof 2005, Yazback 2007). The accumulated pressure for adequacy-based school programs in Ohio led to the PAthway to Student Success (PASS) program that is specifically applied to the formulas of state aid to local school districts. However, this Ohio version of an EBM approach, PASS, was short-lived. It was implemented only for FY 2010 and FY 2011 (Ohio Legislative Service Commission 2011).

The primary goal of this paper is to assess the impact of *repealing* PASS on educational outcomes in local Ohio school districts. As PASS exemplifies an adequacy-based program that is also supposed to enhance outcome *equity*, this paper investigates whether and how repealing PASS affects outcome equity as well. Finally, this paper evaluates whether and how repealing PASS affects fiscal neutrality or equity because PASS retained some provisions to enhance fiscal equity.

Previous studies on the EBM approach show that schools with exceptional educational achivements share in common what the EBM approach suggests as the factors for enhanced student learning. Therefore, they are anecdotal case studies. In contrast, this paper analyzes how an "actual" policy, state aid based on specific EBM-based formulas to local school districts in Ohio, affects student learning. This paper employs Entropy Balancing (Hainmueller 2012, Hainmueller and Xu 2013) to construct an enhanced pre-post study analysis using data from FY 2010 to FY 2019. Empirical findings reveal that repealing Ohio's PASS tends to decrease student performance, detracts from fiscal equity, but unexpectedly enhances outcome equity.

Section 2 provides a short review of outstanding studies on fiscal equity and outcome equity. Section 3 introduces the mechanisms of the EBM approach, some case studies on the effectiveness of the EBM approach, and the programmatic details in Ohio's PASS. Section 4 explains data and Entropy Balancing used for this paper. Section 5 reports main findings, followed by conclusions.

2 School Finance Reforms on Fiscal Equity and Outcome Equity

Various studies empirically show that court-mandated school finance reforms (SFRs) significantly enhanced fiscal equity over school districts in most states up to the early 1990s (Evans, Murray and Schwab 1997, Murray, Evans and Schwab 1998, Corcoran and Evans 2015, Hoxby 2001, Munley and Harris 2010). Jackson, Johnson, and Persico (2016) show that court-ordered mandates and related legislative SFRs in 28 states between 1971 and 2010 significantly improved educational attainment and adult labor market outcomes, with the improvement more pronounced for low-income children.

Even during the Adequacy of Education era since 1990, SFRs in several states have pursued fiscal equity rather than outcome equity. Duncombe and Johnston (2004) show that the foundation aid of 1992 in Kansas dramatically improved the fiscal equity in the state-set foundation level in school spending. Hyman (2017) and Cullen and Loeb (2004) show that Michigan's Proposal A, a modified foundation system, of 1994 sharply improved the fiscal equity across school districts until the early 2000s. However, Hyman (2017) also finds that Proposal A damaged outcome equity at the district level and fiscal equity at the school level. Imazeki and Reschovsky (2004) report that the Foundation School Program (FSP) of 1993 in Texas significantly improved fiscal equity across school districts between 1988 and 2001. Downs (2004) indicates that Act 60 of 1997 in Vermont substantially enhanced fiscal equity across towns and school districts by 2002. Interestingly, outcome equity also improved across school districts. However, fiscal equity was somewhat damaged by 2011 (Picus, Goertz and Odden 2015).

Lafortune, Rothstein, and Schanzenback (2018) conduct an analysis of post-1990 SFRs (i.e., the Adequacy of Education era) up to 2011. SFRs increased per pupil state aid primarily in the lowest income quintile districts. In addition, the student achievement test scores for under-performing districts substantially increased after SFRs. However, there is one caveat in this study. The sixty four SFRs in 26 states analyzed in the study include those based on either fiscal equity or adequacy of education.

Some studies have narrowed down to SFRs based on adequacy of education. In 1997, the New Jersey Supreme Court mandated the state legislature to equalize school funding across school districts, especially between urban poor districts and wealthy districts (Candelaria and Shores 2019, Picus, Goertz and Odden 2015). Picus, Goetz, and Odden (2015) report that even this adequacy-based school aid improved only fiscal equity across the school districts between 1985 and 2008. However, the School Finance Reform Act (SFRA) of 2008 dropped any special funding for the poor districts. As a result, the spending disparity between the poor districts and wealthy districts started widening again.

Candelaria and Shores (2019) conduct a comprehensive analysis of post-1990 SFRs between 1991 and 2010 in 13 states where states' SFRs were strictly tied to adequacy of education grounds. They investigate the causal relationship between court-ordered SFRs, and fiscal resources and student outcomes at the school district level. In sum, fiscal equity did not significantly improve.

However, graduation rate significantly improved overall but the improvement was stronger in poorer school districts. Thus, adequacy-based SFRs show stronger impacts on educational outcomes and outcome equity as one can expect.

3 Evidence-Based Model (EBM) in School Aid

3.1 EBM approaches to school funding

During the Adequacy of Education era since 1990, state courts and legislatures have required that state school finance systems provide an 'adequate' level of educational funding that allows school districts and schools in a state to deploy a range of "educational programs and strategies that would provide each student an equal opportunity to meet the state's education performance standards" (Odden, Goetz and Picus 2007, 4). The adequacy of education centers on improving student performance in the longer term, typically four to six years after implementing adequacy-based programs and strategies (Odden, Picus and Goetz 2010).

According to Odden, Goetz, and Picus (2007), there are approximately four methods to determine school finance adequacy: the cost function approach, the successful district approach, the professional judgment approach, and the evidence-based model (EBM) approach. Odden and Picus (2018) identify ten general but core strategies found in the EBM approach:

- Analyzing student data to understand performance issues and the nature of the achievement gap
- Setting high educational goals such as educating at least 95 percent of the students to exceed a certain performance bar in various subject areas
- Reviewing evidence on good instruction and effective curriculum
- Investing in teacher training
- Extra help for struggling students
- Restructuring the school day for more effective instruction
- Data-based decision making
- Creating professional cultures for good teaching and administration

- Introducing external professional knowledge into schools
- Recruiting best-talented teachers

3.2 Case studies on the effectiveness of the EBM approach

As introduced in Section 2, state aid systems in Vermont significantly improved both fiscal and outcome equity. Picus et al. (2012) provide more details. Between 2001 and 2012, Vermont students' scores on the National Assessment of Educational Progress (NAEP) test ranked among the top ten in the nation although the NAEP scores on math and reading for fourth and eighth grade students were below the national average. Student performance on most dimensions of the New England Common Assessment Program (NECAP) modestly increased and a steady increase in high school graduation rate was reported. In addition, fiscal equity and outcome equity significantly improved during the period. Interestingly, Picus et al. (2012) report that five schools made significant improvements in NECAP reading and math tests between 2005 and 2010. They found 11 common themes across the five schools, which are very similar to the ten core strategies in the EBM approach.

Picus et al. (2013a) assess the impact of Maine's adequacy-based school funding. Maine has distributed state and local tax revenue sources to local school districts based on an adquacy model since 2006. Student achivements in 2011 in Maine's NAEP scores in math and reading were not impressive enough. However, four-year high school graduation rate was slightly above the national average. Fiscal equity across school districts somewhat improved. Picus et al. (2013b) additionally show, albeit with selected schools, that Maine's adequacy-based school funding somewhat improved outcome equity as well. Between 2010 and 2012, five schools significantly improved in math, reading, and science scores on NECAP tests while 62 percent of their students were economically disadvantaged. Picus et al. (2013b) also find that the five schools employed the pedagogical approaches similar to the ten core strategies in the EBM approach.

3.3 Ohio's PAthway to Student Success (PASS)

Ohio has pursued the adequacy-based school funding following the KERA of 1990. In 1997, the Ohio Supreme Court ruled that Ohio's public school funding system was unconstitutional in that the school system in local Ohio school districts did not provide an equitable and adequate base funding necessary to meet academic goals. Subsequent Ohio Supreme Court rulings in 2000, 2001, and 2002 affirmed the earlier ruling based on the adequacy of education (Johnson and Vesely 2017, Simon 2015, Obhof 2005, Yazback 2007). These accumulated court-ordered calls for adequacy-based school funding led Ohio to apply the EBM approach to the formulas of state aid to local school districts since FY 2002 (Appendix A). During FY 2010 and FY 2011, Ohio's EBM-based foundation funding system relied on much more detailed programmatic cost allocations that are closer to the typical EBM strategies noted in Section 3.1, which is called, the PAthway to Student Success (PASS) program.

PASS has eight main funding components to determine state-defined basic education cost. Under each of the eight components, detailed formulas are presented based on the EBM approach. For instance, the number of core teachers for grades K through 3 is computed as Average Daily Membership (ADM) divided by 19. State aid amounts are determined based on these detailed computation formulas that are developed from previous research findings (Ohio Legislative Service Commission 2011).

Another peculiar aspect of PASS is the educational challenge factor (ECF) that is the same wealth measure applied in the parity aid in the previous school funding formulas (Appendix A). The ECF is based on three factors: college attainment rate, poverty rate, and per pupil wealth.

Districts with relatively lower levels of college attainment rate and per pupil wealth but higher poverty rates are likely to receive larger amounts of adequacy-based state aid (Ohio Legislative Service Commission 2011, Ohio Education Department 2010a). Therefore, PASS also intends to maintain fiscal equity as well as outcome equity across school districts.

Beginning from FY 2014, a new foundation formula was applied to the state aid to local school districts. For FY 2012 and FY 2013, a transitionary funding system, Bridge Formula, was implemented (Appendix A). Both formulas are similar to each other in that they are more wealth-neutralizing, which are found in typical state aid formulas during the era of fiscal equity from the early 1970s to 1990 (Ohio Education Department 2013, Ohio Education Department 2010b, Ohio Education Department 2010a). Although PASS was repealed after FY 2011 and short-lived, PASS amounted to the culmination of the adequacy-based policies in Ohio since FY 2002. As a result, analyzing the impacts of repealing PASS is virtually the same as analyzing how the termination of the adequacy-based policies affects student learning, outcome equity, and fiscal equity.

4 Data and Model

4.1 Data

This paper uses fiscal, student demographic, administrative, and student performance data for about 609 local Ohio school districts from FY 2010 to FY 2019 because student performance data for FY 2020 are not available due to COVID-19. After dropping missing cases, there are 6,066 observations for all the variables in Table 1. All dollar values are converted to 2019 constant dollar values, using the state and local government price deflator. The first target outcome should be student performance results because adequacy-based school funding attempts to boost students' educational achievement. Thus, pis in Table 1 is Performance Index Score that is a composite proficiency measure of students' educational performance, which is constructed from various test scores across different subject areas for various grades. Data for pis come from a series of *Ohio School Report Cards*.[1] Mean pis value is about 94.5 points with the minimum value of about 52 points and the maximum value of about 113 points for the entire study period. pis is also used to assess the impact of Ohio's PASS on 'outcome' equity.

As noted earlier, Ohio's PASS also contains features of fiscal equity (e.g., the ECF). As a result, this paper also analyzes first, the impact of PASS on totexp (per pupil total expenditure) and stateaid (per pupil formula aid) and second, on fiscal equity. Data for totexp and stateaid come from a series of *District Profile Report*.[2] Mean totexp value is about 11,608.7 dollars. Mean stateaid value is about 4,529.3 dollars. The minimum value of stateaid is negative (e.g., -194.4) because for some years negative aid exists for a few wealthy school districts due to the recapturing nature of a typical foundation aid. The three variables, pis, totexp, and stateaid, are the main "target" variables in this paper.

The remaining variables are the covariates that are approximately comprised of student characteristics, revenue capacity, and staff capacity in school districts. All these variables come from *District Profile Report*. nonwhite (% of nonwhite students), limiteng (% of students with limited English), and disability (% of students with disability) tap the student characteristics. Four variables measure the district revenue capacity. rev_mill is per pupil property tax revenue raised by one mill. Therefore, it is a standardized measure of property-based local revenue capacity. medinc is median income in school districts.[3] fed_rev is per pupil federal aid revenue. tax_effort

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[1] https://reportcard.education.ohio.gov/download [accessed April 25, 2021]
[2] http://education.ohio.gov/Topics/Finance-and-Funding/School-Payment-Reports/District-Profile-Reports [accessed April 25, 2021]
[3] There is one caveat. For FY 2013, for instance, *District Profile Report* uses property valuation for TY (Tax Year) 2012. To be consistent with this approach in the data file, median income for TY 2012 is matched to FY 2013.

is a local tax effort index that the Ohio Education Department developed. This index is a complex composite measure of school district residents' effort to support public school education. It is based on school income tax and some property taxes, linked to the federal adjusted gross income.[4] teachersal and adminsal measure salary levels for teacher and administrator, respectively. log_ada is logged Average Daily Attendance.

4.2 Model: covariate balancing

Data sets, which provide nationally standardized test scores like the NAEP achievement measures, might be a better choice for this paper because the NAEP measures provide standardized test scores for desirable potential control units (i.e., school districts in other states that have not experienced a program similar to Ohio's PASS). However, the NAEP measures are provided only for odd-numbered years. In addition, they provide test scores for selected school districts in each state (NCES 2017), which might cause selection bias. Thus, it is difficult to find data sets that provide standardized achievement measures for the entire local Ohio school districts and the districts in potential control states. The advantage of using pis for local Ohio school districts is that pis is provided for the entire school districts. As a result, this paper attempts to construct an enhanced pre-post design by applying covariate balancing methods.

Many methodological approaches have recently attempted to balance covariates between two different samples such as treatment and control units to make them as close to each other as possible (Hainmueller 2012, Hainmueller and Xu 2013, Zeng, et al. 2021, Zubizarreta 2015). Note that if we balance (or weight) covariates of control units toward treatment units, the balanced results generate what is widely known as counterfactual treatment units, as explained below.

[4] The formula is too complex to report here. Readers are referred to the URL for *District Profile Report* for the details of the formula.

Among these covariate balancing methods, Entropy Balancing (EB) balances the constraints imposed on the covariate moment conditions of the reweighted control units (Hainmueller and Xu 2013, Hainmueller 2012). EB estimates the counterfactual mean of target outcomes, Y, as follows:

$$\mathbb{E}[\boldsymbol{Y(0)}|\boldsymbol{D=1}] = \frac{\sum_{\{i|\boldsymbol{D=0}\}} \boldsymbol{Y_i w_i}}{\sum_{\{i|\boldsymbol{D=0}\}} \boldsymbol{w_i}} \quad \text{EQUATION 1}$$

, where $D = 1$ indicates certain unit i received treatment or intervention, $D = 0$ denotes control status, and w is the weight to balance covariates between treatment and control units. $[Y(0)|D = 1]$ is potential outcomes of treatment units if they did not receive treatment. The weight, w, is chosen based on the following scheme:

$$\boldsymbol{min_{w_i}} = \sum_{\{i|\boldsymbol{D=0}\}} \boldsymbol{h(w_i)} \quad \text{EQUATION 2}$$

subject to

$$\sum_{\{i|\boldsymbol{D=0}\}} \boldsymbol{w_i c_{ri}(X_i)} = \boldsymbol{m_r} \text{ with r} \in 1,\ldots, \text{R} \quad \text{EQUATION 3}$$

$$\sum_{\{i|\boldsymbol{D=0}\}} \boldsymbol{w_i} = \boldsymbol{1} \text{ and } \boldsymbol{w_i} \geq \boldsymbol{0} \text{ for all } i \text{ such that } \boldsymbol{D=0} \quad \text{EQUATION 4}$$

Equation 3 succinctly explains the key target of EB. $c_{ri}(X_i)$ denotes control units' r moment conditions over a vector of covariates, X_i. In Table 1, for instance, there are ten covariates except for the three target variables (pis, totexp, and stateaid). Then, the moment conditions are weighted by the EB weight, w_i, so that the reweighted covariate moment conditions of the control units become closest to the r moment conditions of treatment units, m_r. $h(w_i)$ in Equation 4 is a distance metric to minimize such that the reweighted control units are as close to treatment units as possible in terms of the covariate vector. Equation 4 is normalization and non-negativity constraints for the weight. This paper balances the ten covariates by the first moment (e.g., mean) and the second moment (e.g., variance). Hainmueller (2012) and Hainmueller and Xu (2013) show that EB generates impact estimators close to true estimators reported from earlier randomized controlled trials (RCTs).

The above EB scheme weights control units to represent treatment units. The mean difference between observed outcomes of treatment units and the counterfactual outcomes generated from covariate balancing in the EB scheme is the Average Treatment Effect on the Treated (ATT). In contrast, if we weight treatment units to represent control units, we are attempting to compute the Average Treatment Effect on the Controls (ATC) (Hainmueller 2012, Zubizarreta 2015). This paper weights treated units (i.e., local Ohio school districts during FY 2010 and FY 2011 when OH PASS was implemented) to represent control units (i.e., school districts after FY 2011 when OH PASS was repealed) to investigate the impacts of "*repealing*" OH PASS. In other words, the above EB scheme first attempts to construct counterfactual school districts from those "before" repealing OH PASS so that the counterfactual districts are closest to those "after" repealing OH PASS in terms of the ten covariates to their second moment conditions. Then, difference in target outcomes between the counterfactual school districts and those after repealing OH PASS presents clues on the impacts of repealing OH PASS on the target outcomes. In short, the EB approach attempts to minimize the potential difference in the pre-event and post-event samples in terms of some moment conditions of the ten covariates. Then, by using the EB weight, w_i, the EB approach estimates the impacts of repealing OH PASS on pis, totexp, and stateaid.

5 Findings

The empirical findings from the EB models indicate that repealing PASS lowers student performance, damages fiscal equity, but unexpectedly boosts outcome equity.

5.1 Impacts of repealing OH PASS on student performance and school spending

Table 2 reports the Average Treatment Effect on the Controls (ATC), which repealing OH PASS propagates. For 2012, for instance, treatment units (local school districts during FY 2010 and FY 2011 when PASS was implemented) are reweighted to represent control units in FY 2012. Thus, the reweighted units construct counterfactual control units: *what might have happened to control units if they received the treatment* (i.e., OH PASS). Then, the difference in the mean outcome values and the counterfactual control units measures the impacts of repealing OH PASS. To avoid the failure of convergence in Entropy Balancing (EB) models, most variables are scaled between 1 and 10. These reweighted samples are used for running survey-design-based weighted regression analysis, with outcome values for each of the control units and the counterfactual units as dependent variable and oh_pass_0 as the independent variable where oh_pass_0 = 1{OH PASS is repealed}.[5] Then, we can repeat the regression analysis with the FY 2013 outcome values of control units and the counterfactual outcomes to estimate ATC for FY 2013, and so on for all the remaining years up to FY 2019, respectively.

The value of the constant for 2012 indicates that if control units (e.g., school districts in FY 2012) received the treatment, pis might have been 97.78 (= 9.778 * 10 to retrieve pis back in the original scale). oh_pass_0 measures the deviation of the "actual, observed" value of pis from 97.78. In FY 2012, pis actually slightly increases by 1.36 points. For FY 2013, pis increases by about 1.7 points. For FY 2014 and FY 2015, pis increases by about 2.37 and 2.64 points, respectively. At first glance, the increase in student performance, pis, seems somewhat unexpected. However, as noted in Section 3.1, EBM approaches generate educational impacts about four to six years later after they are implemented. Ohio already implemented the adequacy-based state funding prior to OH PASS (see Appendix A for formulaic summaries). Therefore, the increase in

[5] Survey-design-based weighted regression models are, by construction, robust against heteroscedasticity.

pis during the four years after OH PASS was repealed, in fact, captures the combined impact of the earlier adequacy-based state funding and OH PASS. However, repealing OH PASS tends to damage student performance starting from FY 2016 until FY 2019: pis decreases by about 7.29 to 11.55 points.

Since totexp and stateaid are used for investigating fiscal equity introduced in Section 5.2, the impacts of repealing OH PASS on totexp and stateaid are briefly summarized here (see also Appendix A for formulaic summaries). Starting from around FY 2016, stateaid (multiply 1,000 to recover original values) increases and totexp (multiply 10,000 to recover original values) increases as well. Since the growth amount of totexp is not as large as that of stateaid, we can infer that locally raised revenues might have decreased because totexp is approximately equal to the sum of stateaid and locally raised revenues.

5.2 Lessons learned: impacts of repealing OH PASS on fiscal and outcome equity

Table 3 reports how repealing OH PASS affects fiscal and outcome equity by using the same reweighted samples based on EB and survey-design-based weighted regression models. This paper uses two fiscal measures: logged median income (ln_medinc) and logged per pupil property tax revenue raised by one mill (ln_rev_mill). All three target variables are also logged: ln_pis, ln_totexp, and ln_stateaid.

The third column shows the elasticity between ln_medinc and ln_stateaid, which measures fiscal equity. int_medinc is an interaction variable of ln_medinc and oh_pass_0. As such, int_medince measures the change in the elasticity between the median income and state aid when OH PASS is repealed. For FY 2012, both elasticity measures are *statistically significant* and negative. Therefore, poorer districts tend to receive larger state aid before and after OH PASS is repealed. This pattern persists until FY 2013 when the new aid funding formula was implemented.

Beginning from FY 2016, however, the elasticity measure associated with int_medinc turns positive. The sixth column shows the elasticity between ln_stateaid and ln_rev_mill. The patterns on fiscal equity are virtually the same as those with ln_medinc except that the interaction between ln_rev_mill and ln_stateaid is statistically significant and positive even for FY 2015. These results overall indicate that fiscal equity somewhat deteriorates after repealing OH PASS. The educational challenge factor (ECF) in OH PASS might have enhanced fiscal equity more than the 2014 funding formula did.

The literature of education finance generally indicates that wealthier districts tend to spend more for students. The second and fifth columns evidence that wealthier districts tend to spend more. For some years after OH PASS is repealed, per pupil total expenditure for poorer districts tends to be higher than their wealthier counterparts. While more research is warranted on this anomalous observation, we may guess that poorer districts might have exerted extra local fiscal efforts to catch up with wealthier districts during the post-PASS years.

The first and fourth columns provide important clues on outcome equity. Wealthier districts tend to experience higher student performance but there is one unexpected observation. Both int_medinc and int_rev_mill show that beginning from FY 2016, when repealing OH PASS starts damaging student performance as reported in Section 5.1, the elasticity measures turn negative, which are also statistically significant. As student performance decreases, outcome equity surprisingly improves: poorer districts experience higher student performance. However, this somewhat surprising observation is not totally unexpected.

As introduced in Section 3.2, some poor school districts in Vermont have significantly improved student learning by adopting educational strategies akin to what typical EBM plans recommend. However, the adoption of EBM-like strategies was voluntary and there was no statewide legislation that imposes EBM strategies in the way OH PASS did for FY 2010 and FY 2011. As also introduced in Section 3.3, OH PASS is based on detailed categories of educational spending, which are legislatively defined and recipient school districts do not have much discretion for moving fund around. Lafortune, Rothstein, and Schanzenbach (2018) show that increased school spending from SFRs boosts student performance. However, poorer districts use almost half of the funding for capital spending. In contrast, OH PASS, similar to typical EBM strategies, focuses more on instructional spending.[6] Thus, OH PASS might have invited extra rigidity in utilizing funding for what poor school districts might need. Once OH PASS is repealed, the poor districts might have more discretion on their funding choices, which improves their student performance (e.g., negative elasticity measures since FY 2016).

6 Conclusions

Since 1990 when the KERA of 1990 was legislated, many states have endeavored to equalize educational outcomes rather than fiscal outcomes in what has been known as the Adequacy of Education era. As a result, the states have pursued adequacy-based educational strategies and programs. The Evidence-Based Model (EBM) is one of the adequacy-based programs. While some local school districts in selected states opted for EBM strategies, Ohio actually legislated specific EBM strategies into Ohio's PAthway to Student Success (PASS). This paper investigates whether and how OH PASS affects student performance after it was repealed beginning from FY 2012. It also assesses the impacts of repealing OH PASS on fiscal and outcome equity by using Ohio school district data from FY 2010 to FY 2019. The empirical findings in this paper show that after

[6] For FY 2010 and FY 2011, 76.86 percent of the total PASS funding was assigned to Instructional Services Support (Ohio Education Department 2010b)

repealing Ohio's PASS student performance deteriorates, fiscal equity worsens, but outcome equity unexpectedly improves.

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Appendix A

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 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
pis	6,066	94.483	9.431	52.114	113.013
totexp	6,066	11,608.670	2,093.410	0.000	25,734.610
stateaid	6,066	4,529.299	2,214.714	-197.356	14,773.380
nonwhite	6,066	0.140	0.181	0.000	1.000
limiteng	6,066	0.011	0.028	0	1
disability	6,066	0.138	0.033	0.042	0.279
rev_mill	6,066	163.068	75.171	44.930	1,062.330
medinc	6,066	37,895.770	8,923.240	13,744.000	86,816.050
fed_rev	6,066	931.449	505.843	0.000	4,373.278
tax_effort	6,066	1.019	0.355	0.227	3.340
teachersal	6,066	60,599.800	9,357.810	0.000	130,720.000
adminsal	6,066	82,607.670	54,990.510	0.000	4,076,264.000
log_ada	6,066	7.506	0.840	5.250	11.191

Table 2: ATC after Entropy Balancing

	Dependent variable:		
	pis	totexp	stateaid
	(1)	(2)	(3)
2012			
oh_pass_0	0.136***	0.018***	-0.238**
constant	9.778***	1.126***	4.375***
Obs	1,826	1,826	1,826
Prob>F	0.002	0.342	0.016
R2	0.012	0.002	0.003
2013			
oh_pass_0	0.170***	-0.033*	-0.418***
constant	9.713***	1.127***	4.457***
Obs	1,827	1,827	1,827
Prob>F	0.000	0.051	0.001
R2	0.019	0.006	0.012
2014			
oh_pass_0	0.237***	0.050	-0.105
constant	9.674***	1.086***	4.292***
Obs	1,826	1,826	1,826
Prob>F	0.001	0.106	0.562
R2	0.037	0.013	0.001
2015			
oh_pass_0	0.264***	-0.016	0.393*
constant	9.651***	1.156***	4.029***
Obs	1,814	1,814	1,814
Prob>F	0.001	0.667	0.095
R2	0.004	0.001	0.010
2016			
oh_pass_0	-1.155***	0.034	0.820***
constant	9.729***	1.126***	4.047***
Obs	1,824	1,824	1,824
Prob>F	0.000	0.140	0.000
R2	0.337	0.006	0.036
2017			
oh_pass_0	-0.771***	0.043*	0.938***
constant	9.644***	1.140***	4.076***
Obs	1,825	1,825	1,825
Prob>F	0.000	0.094	0.000
R2	0.188	0.009	0.004
2018			
oh_pass_0	-0.748***	0.081**	0.889***
constant	9.648***	1.097***	4.050***
Obs	1,825	1,825	1,825
Prob>F	0.000	0.023	0.000
R2	0.177	0.032	0.040
2019			
oh_pass_0	-0.729***	0.098***	0.956***
constant	9.666***	1.110***	3.975***
Obs	1,825	1,825	1,825
Prob>F	0.000	0.004	0.000
R2	0.168	0.043	0.045

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Equity after Entropy Balancing

	Dependent variable:						
	ln_pis (1)	ln_totexp (2)	ln_stateaid (3)		ln_pis (4)	ln_totexp (5)	ln_stateaid (6)
2012							
ln_medinc	0.198***	0.058**	-1.659***	ln_rev_mill	0.056***	0.149***	-1.324***
int_medinc	0.011***	0.001	-0.061***	int_rev_mill	0.030***	-0.002	-0.114
constant	2.015***	0.043	3.541***	constant	2.258***	0.065***	1.823***
Obs	1,826	1,824	1,823	Obs	1,826	1,824	1,823
Prob>F	0.000	0.114	0.000	Prob>F	0.000	0.000	0.000
R2	0.434	0.005	0.312	R2	0.170	0.105	0.622
2013							
ln_medinc	0.193***	0.039	-1.604***	ln_rev_mill	0.058***	0.130***	-1.212***
int_medinc	0.014***	-0.030***	-0.109***	int_rev_mill	0.037***	-0.036	-0.223***
constant	2.016***	0.065	3.491***	constant	2.254***	0.058***	1.761***
Obs	1,827	1,826	1,825	Obs	1,827	1,826	1,825
Prob>F	0.000	0.000	0.000	Prob>F	0.000	0.000	0.000
R2	0.428	0.016	0.328	R2	0.192	0.060	0.582
2014							
ln_medinc	0.173***	0.027	-1.691***	ln_rev_mill	0.025	0.102***	-1.295***
int_medinc	0.021***	0.013	-0.038	int_rev_mill	0.067***	0.022	-0.019
constant	2.042***	0.063	3.517***	constant	2.259***	0.066***	1.772***
Obs	1,826	1,825	1,822	Obs	1,826	1,825	1,822
Prob>F	0.000	0.292	0.000	Prob>F	0.000	0.000	0.000
R2	0.363	0.005	0.314	R2	0.178	0.073	0.551
2015							
ln_medinc	0.190***	0.187***	-1.930***	ln_rev_mill	0.055***	0.208***	-1.415***
int_medinc	0.022***	-0.029*	0.070	int_rev_mill	0.050***	-0.084**	0.238*
constant	2.017***	-0.092	3.757***	constant	2.245***	0.065***	1.824***
Obs	1,814	1,813	1,811	Obs	1,814	1,813	1,811
Prob>F	0.000	0.001	0.000	Prob>F	0.000	0.000	0.000
R2	0.408	0.053	0.341	R2	0.241	0.134	0.514
2016							
ln_medinc	0.336***	0.009	-1.771***	ln_rev_mill	0.187***	0.107***	-1.368***
int_medinc	-0.091***	0.012	0.115***	int_rev_mill	-0.122***	0.007	0.288***
constant	1.823***	0.111***	3.603***	constant	2.150***	0.081***	1.885***
Obs	1,824	1,822	1,822	Obs	1,824	1,822	1,822
Prob>F	0.000	0.325	0.000	Prob>F	0.000	0.000	0.000
R2	0.530	0.003	0.310	R2	0.239	0.068	0.499
2017							
ln_medinc	0.311***	0.004	-1.898***	ln_rev_mill	0.142***	0.108***	-1.413***
int_medinc	-0.062***	0.013	0.154***	int_rev_mill	-0.066***	-0.006	0.382***
constant	1.862***	0.134***	3.675***	constant	2.170***	0.100***	1.905***
Obs	1,825	1,824	1,822	Obs	1,825	1,824	1,822
Prob>F	0.000	0.308	0.000	Prob>F	0.000	0.000	0.000
R2	0.433	0.003	0.308	R2	0.194	0.065	0.507
2018							
ln_medinc	0.315***	-0.034	-1.893***	ln_rev_mill	0.131***	0.084***	-1.450***
int_medinc	-0.060***	-0.031***	0.148**	int_rev_mill	-0.051***	0.026	0.375**
constant	1.858***	0.155***	3.650***	constant	2.174***	0.089***	1.898***
Obs	1,825	1,824	1,823	Obs	1,825	1,824	1,823
Prob>F	0.000	0.001	0.000	Prob>F	0.000	0.000	0.000
R2	0.427	0.017	0.290	R2	0.163	0.058	0.494
2019							
ln_medinc	0.310***	-0.049*	-1.868***	ln_rev_mill	0.125***	0.078***	-1.409***
int_medinc	-0.057***	0.042***	0.163***	int_rev_mill	-0.051***	0.042*	0.390***
constant	1.862***	0.183***	3.621***	constant	2.178***	0.101***	1.896***
Obs	1,825	1,824	1,823	Obs	1,825	1,824	1,823
Prob>F	0.000	0.000	0.000	Prob>F	0.000	0.000	0.000
R2	0.426	0.029	0.300	R2	0.159	0.063	0.499

Note: *p<0.1; **p<0.05; ***p<0.01