Impact of Implementing Weighted School Funding on High School Educational Attainment

Alice Martynova

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Abstract

Since 1993, many large school districts across the United States have shifted away from de ploying federal funds to schools based on uniform staffing formulas and have instead adopted weighted school funding (WSF). WSF provides a fixed-dollar amount to schools for each stu dent type, with larger increments going to students from low-income backgrounds, those with special needs, and/or those who are English-language learners. In this study, I used publicly available NCES data to study the impact of WSF on high school graduation rates, dropout rates, and pupil-per-teacher ratio. The difference-in-difference empirical strategy finds that WSF has limited statistically significant impact on any of these educational attainments. These results suggest that WSF's effects still need to be further studied to fully understand the power and drawbacks of this new and emerging funding schematic.

1 Introduction

Over the last two decades, many large school districts across the United States have shifted away from deploying federal funds to districts based on uniform staffing formulas to allocating funds to individual schools within the district based on the particular mix of students at each school. This new funding strategy, known as weighted student funding (WSF), deploys a fixed-dollar amount to schools for each student type with larger increments going to students from low-income backgrounds, those with special needs, and/or those who are English language learners. It is worth noting that WSF does not change the total amount of money a district receives; rather, it alters how the funds are distributed amongst the schools within the district.

New funding methods, like WSF, have the potential to fight the poverty cycle, reduce inequality, and have significant effects on student educational outcomes.[1] This paper examines how WSF affects high school educational attainments, particularly graduation rates, dropout rates, and pupil-per-teacher ratio. Although testing this hypothesis is challenging due to the limited number of schools that have adopted WSF and the limited quantity of public data, the available data provides for robust empirical tests to better understand WSF's potential.

To understand the effect on high school district graduation rates, dropout rates, and pupil-per-teacher ratios, this paper implements a staggered difference-in-difference for each educational attainment to compare outcomes at control schools that never implemented WSF to treated districts that implemented WSF between 1995-2018. The treated group consists of the 27 WSF school districts documented in the U.S. Department of Education report. The control districts are chosen from the NCES annual table of "Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students." By only selecting districts from this category, I guarantee districts have similar sizes and are nationally representative which leads to more robust results.

The study concludes positive but mostly insignificant effects of WSF on graduation rates and pupil-per-teacher ratio and inconclusive negative effects on dropout rates. Following treatment, the pupil-per-teacher ratio and graduation rates remain unchanged relative to the pre-treatment mean and both effects are statistically insignificant. In addition to NCES documented graduation rates, this paper introduces a new statistic, "pseudo-graduation" rate, which is calculated by dividing the number of graduates by total district enrollment. WSF increases pseudo-graduation rates by about 0.3 percentage points which is an overall 6% increase, but this is only at the 10% significance level and must be interpreted with caution. Finally, WSF appears to decrease dropout rates by 1 percentage point which is an overall 11% decrease.

[1] Johnson, Rucker C., and C. Kirabo Jackson. "Reducing Inequality through Dynamic Complementarity: Evidence from Head Start and Public School Spending." American Economic Journal: Economic Policy 11, no. 4 (November 2019): 310–49. https://doi.org/10.1257/pol.20180510.

Nonetheless, this result must be interpreted with caution as the dropout rate regression does not satisfy the parallel trend assumption (further discussed in Sections 4 and 5). Although there is no apparent sizable and significant effect, WSF does not negatively affect any educational attainment at the district level which questions theories that WSF has an overall harmful impact.

The current WSF literature only focuses on describing the WSF model and studying its impact on standardized test scores; furthermore, many WSF studies use datasets that limit the robustness and interpretation of results. For instance, a National Study by the U.S. Department of Education focuses on describing WSF policy, its intended changes and bene fits, and details school districts that adopted WSF before 2018.[2] However, it does not quantify the effect on educational attainments. Another paper focuses on understanding the financial details of WSF at the district level, specifically the unique weight formulation of each district and whether the formulations are aligned with WSF's goal of increasing equity.[3] While this study begins to scrape at the surface of understanding the academic outcomes of WSF, the Edunomics report notes that the state-level results should be interpreted with caution since WSF districts tend to be different than others in their state in both enrollment size and student composition. Moreover, the effects of WSF cannot be isolated from the effects of other policies implemented around the same time. As mentioned previously, my paper produces more robust results by only selecting treatment and control districts with over 15,000 students from a nationally representative sample.

The rest of the paper is organized as follows. Section 2 provides an in-depth WSF policy debrief. Section 3 presents the data. Section 4 describes the empirical strategy. Section 5 presents the results. Section 6 presents a summary discussion. Section 7

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[2] Johnson, Rucker C., and C. Kirabo Jackson. "Reducing Inequality through Dynamic Complementarity: Evidence from Head Start and Public School Spending." American Economic Journal: Economic Policy 11, no. 4 (November 2019): 310–49. https://doi.org/10.1257/pol.20180510.

[3] Chicago Public Schools, Indianapolis Public Schools, Milwaukee Public Schools, Newark Public Schools, and Springfield Empowerment Zone. "Lessons Learned: Weighted Student Funding," 2020.

details future work, and Section 8 concludes the paper.

2 Policy Background

Historically U.S. school districts distribute federal funds to schools through tangible resources rather than allocating specific dollar amounts to individual schools. These traditional uniform staffing allocation systems typically determine the number of teachers, school administrators, and other types of staff for each school based on its total student enrollment. However, many educators and researchers have noted that these systems can contribute to and increase inequity amongst schools, especially those with higher concentrations of at-risk students may not receive additional resources to meet their complex needs.[4]

To mitigate these inequities, the WSF Federal Government program allows districts to deploy a fixed-dollar amount to schools for each student type with larger increments going to students from low-income backgrounds, with special needs, and/or who are English-language learners. Under the WSF approach, districts may allocate resources more effectively to meet the specific needs of each of their school's students.

Policymakers from the federal government to the district level are always researching and creating new programs and funding methods to improve public education. Districts choose to adopt WSF to increase equity, transparency, flexibility, and school-level autonomy to focus on improving student outcomes.[5] WSF has been around since 1995 and over the past 2 decades, 27 school districts have implemented WSF with these goals in mind. This paper sets out to understand whether WSF indeed improved student educational outcomes. This is relevant today as Biden plans to double funding for K-12 education through the "Build Back Better" plan as schools struggle to successfully emerge out of the pandemic and help students meet standards following

[4] Rubenstein, Ross, Amy Schwartz, and Leanna Stiefel. "Rethinking the Intradistrict Distribution of School Inputs to Disadvantaged Students," 2006.
[5] Chicago Public Schools, Indianapolis Public Schools, Milwaukee Public Schools, Newark Public Schools, and Springfield Empowerment Zone. "Lessons Learned: Weighted Student Funding,"

the past year of virtual learning.[6] Understanding the effects of WSF can help schools and the federal government use their budget effectively.

3 Data

To study the impact of implementing WSF on high school educational attainment through a difference-in-difference model, I need funding data at the district level to understand which districts implemented WSF as well as school district performance data. Both datasets are further detailed below.

To identify control and treated districts, I will rely on the findings of existing WSF litera ture. The U.S. Department of Education made a detailed 2019 WSF report (Levin, Manship, Hurlburt, and Atchison 2019) which includes a table of 27 well-documented districts that have implemented WSF and have continued to use it, along with the year in which they implemented it. "Lessons Learned: Weighted Student Funding," (2019-Present) report provides a similar table of 18 districts that have implemented WSF, and these 18 districts align with the 27 districts provided by the U.S. Department of Education. I use both lists to develop my treatment group. However, both WSF papers, anonymize schools that did not implement WSF in creasing the difficulty of creating a control group. Through direct discussion with Hannah Jarmalowski, a Research Fellow at Georgetown Edunomics Lab, she explained that there are very few districts that have implemented WSF and districts that have are documented in the literature. I use the limited existing literature to create a thorough table of WSF im plementing school districts (Table 1) and have confidence that unlisted districts have never implemented WSF.

To explore multiple levels of educational attainment, the main data resource will be the NCES, the National Center for Education Statistics. The NCES provides annual

[6] Camera, Laura. "Biden's Budget Significantly Boosts K-12 Education Spending." U.S. News, April 9, 2021. https://www.usnews.com/news/education-news/articles/2021-04-09/bidens-budget-significantly-boosts-k-12-education-spending.

tables of "Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students" from 1995-2018. The pupil per teacher ratio is one of the only variables available every year from 1995-2018. It is important to note that the ratio itself is not a measurement of educational attainment, but in the literature, lower pupil per teacher ratio is correlated with higher educational achievement.[7] The NCES tables also contain high school dropout rates by district from 1996-2009. Although this does not cover up to 2018, there are 9 schools that adopted WSF around 2002 and dropout rates can be observed for those sub-selected districts. The NCES also documents high school graduation rates by district from 2007 to 2018, and this data can be used for the 10 schools that adopted WSF between 2007 and 2018. Note intuitively it should be possible to get graduation rates from 1996-2009 by using 1-dropout rate, but for 2007 and 2008 in which both graduation and dropout rates are available, graduation rates are not equivalent to 1-dropout rates.

Due to changes in data collection methods, it is difficult to find consistent data measure ments over the past 25 years. The NCES does provide the number of high school graduates at the district level from 1995 to 2009, but this raw number is unusable because it does not separate number of graduates from national migration changes and general population growth. In addition to the number of graduates, the NCES provides the total enrollment count at every district. As a rough estimation, I divide the number of graduates by total enrollment to get a "pseudo-graduation" rate from 1995 to 2009.

To perform a robust staggered difference-in-difference, the data must be divided into treated and control groups using information from the U.S. Department of Education report and NCES. The treated group for each educational attainment will be selected from the 27 WSF school districts documented in the U.S. Department of Education report. I do not use all 27 school districts currently implementing WSF as the

[7] Jackson, C. Kirabo, Rucker C. Johnson, and Claudia Persico. “The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms.” Working Paper. Working Paper Series. National Bureau of Economic Research, January 2015. https://doi.org/10.3386/w20847.

Minneapolis School District implemented WSF in 1993 and the Prince William County Public Schools implemented WSF in 1994, but there is insufficient NCES data prior to 1995. Atlanta Public Schools and Shelby County Schools districts implemented WSF in 2018, but NCES has yet to upload the needed data beyond 2018. Following these adjustments, the treated group is selected from a pool of 23 districts. The control districts will be chosen from the NCES yearly table of "Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students." Only districts with consistent data for the respective time-period for each attainment will be chosen.[8] All the districts will be from this table since most WSF implementing districts are large urban school districts, and the NCES only provides district-level statistics on districts with more than 15,000 students. Summarizing the NCES data reveals the number of treated and control observations for every educational attainment. Table 2 summarizes the pupil-per-teacher ratio, dropout rate, graduation rate, and pseudo-graduation rate by control and treatment group. Notice that dropout rate has the greatest number of observations (total and by control/treated) even though it does not cover the full period from 1995-2018 because it does not omit treated or control districts that are missing data for any year in between 1996-2009. On the other hand, the other 3 measurements only include data for districts with measurements for every year. This is necessary because there are no treated districts that had dropout data for every year between 1996 and 2009. This effects the interpretation of dropout regression results which will be further discussed in Section 6, the discussion section. Figure 1 visually summarizes the data by graphing arbitrarily chosen districts treated in the same year versus control schools for each educational attainment. Even before running the empirical tests, this figure hints at two findings: parallel trends are likely to be unsatisfied for dropout rates and results for all educational attainments are likely to

[8] For pupil-per-teacher ratio, actual graduation rate, and pseudo-graduation rate, only districts with data for every year will be chosen. The exception is the dropout rate controls because dropout data is not available for every year for any treated district. This will limit the interpretation of the dropout rate results which is further discussed in Section 6.

be small and minimal in effect.

4 Methods

To understand the effect of WSF on various high school educational attainments at the district-level, this study will rely on the difference-in-difference method to compare outcomes at control districts that never implemented WSF and treated districts that implemented WSF between 1995-2018.

Difference-in-difference is the best method, given the available data and nature of WSF implementation across districts, to estimate the educational effects of WSF. However, among the 23 treated school districts, many districts were treated at different times. This makes it difficult to perform a simple regression and a traditional difference-in-difference. Thus, I propose the following regression which should find coefficients on the pre-treated periods are statistically insignificant and hence demonstrate parallel trends leading into the treat ment. The coefficients on post-treated periods will show the effect of WSF on the specific measurement of educational attainment:

$$E_{d,t} = \alpha_d + \delta_t + \sum_{y=0}^{T_1} \gamma_y D_{d,y} + \sum_{y=T_0}^{-2} \gamma_y D_{d,y} + \epsilon_{d,t} \quad \text{(Equation 1)}$$

Where $E_{d,t}$ is the educational outcome for a district d at time t. α_d and δ_t are the district and year fixed effects respectively. ϵ_{dt} is the error term. T_0 and T_1 in the summation are, respectively, the lowest lag year and highest lead year to consider surrounding the treatment period. $D_{d,y}$ is a dummy variable that is equal to 1 if the observation's period relative to district *d*'s first treated period is the same value as *y*; otherwise the dummy is equal to 0 and is 0 for all never-treated observations. The regression coefficients are the γs which are for each year leading and lagging the treatment. Note the −1 is omitted from the summation to avoid multicollinearity and serves as the point of reference.

Equation 1 describes a dynamic regression which will give detailed insight into the effect of WSF on the educational attainment every year after treatment. However, for simplicity of understanding the overall effects of WSF, I will also run a static regression (Equation 2).

$$E_{d,t} = \alpha_d + \delta_t + \beta * (POST_t * TREAT_d) \text{ (Equation 2)}$$

In Equation 2, I regress the outcome for district *d* in year *t* on a dummy variable that is the interaction between $POST_T$ (year *t* is after WSF has been implemented in that district) and $TREAT_d$ (district *d* is a district in which WSF has been or will be implemented). Like in Equation 1, α_d and δ_t are the district and year fixed effects respectively.

Graphing the γ coefficients from Equation 1 will show the sign and size of the treatment, but to be able to effectively interpret these results, several assumptions need to be satisfied. First, the allocation of intervention must not be determined by the outcome; meaning if an increase in educational attainments is found following the implementation of WSF, it is due to the new funding scheme rather than prior characteristics or other novel changes of the school district. This assumption is satisfied because the 23 WSF implementing school districts and the control group are nationally representative. Potential educational attainment changes can be attributed to WSF because it is unlikely multiple schools passed similar policies other than WSF at the same time and achieved similar educational results.

Additionally, there must be no spillover effects from treated to untreated school districts. Historically, school districts are very isolated, and students within one district are within the same city and their education is unaffected by the policies of nearby districts. Furthermore, there have been numerous peer-reviewed, economic studies that have compared various school districts in the same area using a difference-in-difference model.[9]

The most important assumption to satisfy is the parallel trend assumption. As in most economic studies, it is impossible to observe the treatment group in the absence of treat ment. Thus, I will show the γ coefficients leading into treatment in Equation 1 are zero indicating parallel trends into treatment. Graphing these coefficients in Figures 2-5 for all districts across all years reveals the coefficients on the pre-period dummies are statistically indistinguishable from 0. These findings are further discussed in Section 5.

5 Results

This study considers the impact of WSF on high school district pupil-per-teacher ratio, actual and pseudo-graduation rates, and dropout rates. I run the dynamic regression described in Equation 1 and the static regression described in Equation 2 for the selected control and treated districts while accounting for district and year fixed effects. The rest of this section will present the results from the static regression followed by the dynamic regression.

The static regression reveals positive alas only marginally significant effects on pupil-per teacher ratios, actual and pseudo-graduation rates, and harder-to-interpret negative effects on dropout rates. Table 3 shows these raw results of the static regression and illustrates pupil per teacher ratio and graduation rate coefficients are slightly positive but statistically insignificant at the 5% and even 10% level. The effect of WSF on the dropout rate is negative and statistically significant at the 10% level. However, Figure 5, a graph of coefficients on dropout rates from the dynamic regression, clearly shows that parallel trends are unsatisfied for dropout rates, thus these results are not robust. Most notably, the pseudo-graduation rate appears to be slightly positive and to be statistically significant at the 10% level. However, pseudo-graduation is a measurement created for this study and is difficult to interpret. It

9 Harris, Douglas N., and Matthew F. Larsen. “Taken by Storm: The Effects of Hurricane Katrina on Medium-Term Student Outcomes in New Orleans.” Journal of Human Resources 58, no. 5 (September 1, 2023): 1608–43. https://doi.org/10.3368/jhr.58.5.0819-10367R2.

will be further discussed in Section 6.

Dynamically regressing on pupil-per-teacher ratio leads to coefficients of negligible size leading into and lagging out of treatment. Referencing Figure 2, the confidence intervals on the regression coefficients for every lead year cover 0. However, the lagging coefficients also cover 0 and do not seem to have a constant trend which signals that WSF does not have a significant effect on the pupil-per-teacher ratio. Figure 2 was created using Appendix Table A1 which includes raw coefficients and standard errors.

While the pupil-per-teacher regression satisfies parallel trends, the dynamic graduation rate regression shows not all leading coefficients cover 0 in their 95% confidence interval (Figure 3 created using Appendix Table A2). This is likely due to the limited number of treatment schools and smaller time-period compared to the pupil-per-teacher data. Due to the noise of these results, the actual graduation rate results are unusable in identifying the effect of WSF.

WSF appears to have a noticeable effect on pseudo-graduation rates at the 10% signif icance level. Pseudo-Graduation was calculated from 1995-2009 for 4 treated districts and 137 control districts. Starting with satisfying the parallel trends assumption, all leading treatment coefficients in Figure 4 have confidence intervals that cover 0. This helps support the parallel trend assumption leading into treatment. In this case, the lagging coefficients appear to have an upward trend that becomes slightly significant around 6 years after treat ment. Figure 4 was created using Table A3 attached in the appendix which includes raw coefficients and standard errors.

As discussed previously, the dropout rate coefficients are difficult to interpret as they do not satisfy the parallel trend assumption (Figure 5). It is important to note that after treatment, the regression coefficient confidence intervals do follow a negative trend, however, the coefficients continue to cover 0 indicating an absence of a statistically significant effect of WSF on dropout rates.

6 Discussion

Overall, WSF has limited impact in size and significance on high school pupil-per-teacher ratio, actual and pseudo-graduation rates, and dropout rates. As described in the results section, the coefficient on pupil-per-teacher ratio is close to 0 and statistically insignificant. This is not immensely surprising because as noted in the Section 1 and 2, WSF does not increase the total sum of money a district receives. Even though some higher-risk schools within a district may receive additional funding through WSF to invest in more teachers, at the district level and nationally WSF has limited impact on the pupil-per-teacher ratio.

The effect on actual graduation rates is close to null which is unsurprising given the literature on the challenges of improving high school graduation rates. Following treatment, the mean graduation rates rise for treated districts from 62.89 to 63.056 (Table 3) which is a close to 0 effect and statistically insignificant. Again, this is not immensely surprising, as high school graduation rates are historically difficult to improve even through programs targeted at improving graduation rates.[10] Furthermore, graduation rates do not fully satisfy parallel trends making the interpretation less robust (Figure 3). This is likely because there are only 5 treated districts which increases the noise.

Dropout rates slightly decrease following WSF, but it is imminent to remember that dropout rates fail to satisfy parallel trends. Districts that implement WSF appear to decrease dropout rate by about 1% compared to districts that do not implement WSF which is a relative 11% decrease of the pre-treatment mean, at the 10% statistically significant level. However, this result is not robust as the dropout rate regression does not satisfy the parallel trend assumption (Figure 5). Without this vital assumption, there is no definitive conclusion. The data for dropout rates was not panel data which likely

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10 Mac Iver, Martha Abele. “The Challenge of Improving Urban High School Graduation Outcomes: Findings from a Randomized Study of Dropout Prevention Efforts.” *Journal of Education for Students Placed at Risk (JESPAR)* 16, no. 3 (July 2011): 167–84. https://doi.org/10.1080/10824669.2011.584497.

increased the noise of the data leading into treatment. If more data is acquired, parallel trends can be satisfied, and a definitive effect of WSF on dropout rates can be identified.

Finally, I find after implementing WSF, district pseudo-graduation rates increase from 4.32 to 4.616 which is a 6% increase, but there are many limitations to this result. First, it is at the 10% significance level and should be approached with caution. Furthermore, this educational attainment measurement was made for this paper due to limited publicly available district level data. The original goal of the pseudo-graduation rate measurement was to support the results of the effect of WSF on standard graduation rates. However, the pseudo-graduation result should not be fully discarded and rather further studied. Remember pseudo-graduation is equal to the number of graduates divided by total enrollment within a district. Since I found no effect of WSF on graduation rates, WSF increasing pseudo graduation rate could indicate WSF leads to a decrease in total enrollment within a district. This could signal a decrease in high school enrollment which is not necessarily an adverse effect. For example, decreasing high school enrollment within the studied schools could imply migration of families to less urban and crowded schools.

Ultimately WSF has no sizable and significant effects on pupil-per-teacher ratio, dropout rates, graduation rates, and even pseudo-graduation rates. However, even this finding should not be discarded. One major critique of WSF is that it reallocates money from higher-income students to those who are qualified for WSF funding which could negatively impact more privileged students. However, the 95% confidence interval of every coefficient covers 0 which indicates that WSF does not harm the general student population.

7 Future Work

The inconclusive results of this study indicate a need to continue understanding WSF's effect at the level of students directly targeted by WSF. Due to time constraints, I was unable to also explore the effects of WSF at the level of students who are

English-Language learners, have disabilities, or come from low-income backgrounds. After exploring literature and data sets from the Equality of Opportunity project, I identified two promising data sets: the EDFacts data set and Neighborhood Characteristics by County.

The EDFacts data set details the percentage of students in every district who score above proficient on their state's ELA and Math standardized test from 2009-2018, broken down by low income, disability, and English language learner status. The large and complex EDFacts data set needs to be thoroughly processed and separated by control and treatment districts, about 10 treated districts in the given period. The empirical method for standardized testing will follow the same dynamic regression described in Equation 1 in Section 4. Although it is disappointing that the effect of WSF on standardized testing must be left as a future study, there are many drawbacks in current literature that hindered this study from focusing on standardized testing. First, the Georgetown WSF study already explores the effect of WSF on standardized testing. As the purpose of this study was to expand upon WSF's overall effects, I chose to put full focus into exploring other educational attainments. Another reason this study did not focus on testing is over 40 states changed their standardized tests in 2010 with the adoption of national common core increasing the difficulty of isolating the effect of WSF from drastic changes in standardized testing.[11] However, I can try to mitigate this effect by adding a fixed state effect.

It is also important to study the effect of WSF on pupil-per-teacher ratio, actual and pseudo graduation rates, and dropout rates at the low-income level using the Equal Op portunity data source Neighborhood Characteristics by County. This data set details the percentage of low-income county residents. However, this data set is by county, so I would only use control and treated districts that cover full counties and assume that the county level and district level percentage of low-income backgrounds are similar. The

11 Polleck, Jody N, and Jill V Jeffery. "Common Core Standards and Their Impact on Standardized Test Design: A New York Case Study." *The High School Journal* 101, no. 1 (2017): 1–26. https://muse.jhu.edu/pub/12/article/676358.

regression will follow a similar format to Equation 1 from Section 4, but with an additional variable $I_{d,y}$, representing the low-income population percentage in district d and year y (Equation 3). The γ coefficient will find the isolated effect on districts implementing WSF, ρ coefficient will represent the isolated effect on continuous income levels, and σ, our main coefficient of interest, finds the interaction for every year for varying income levels.

$$E_{d,t} = \alpha_d + \delta_t + \sum_{y=T_0}^{-2} \gamma_y D_{d,y} + \sum_{y=0}^{T_1} \gamma_y D_{d,y} + \sum_{y=T_0}^{-2} \rho_y I_{d,y} + \sum_{y=0}^{T_1} \rho_y I_{d,y} + \sum_{y=T_0}^{-2} \sigma_y D_{d,y} * I_{d,y} + \sum_{y=0}^{T_1} \sigma_y D_{d,y} * I_{d,y} + \epsilon_{d,t} \quad \text{(Equation 3)}$$

8 Conclusion

Weighted School Funding has been around for over 2 decades and over 20 districts have implemented the funding policy to solve inequities between students by allocating additional funds to students from low-income backgrounds, who are english-language learners, or who have a disability. However, WSF is largely unstudied, and little is known about its effects on educational attainments. Using available public data, I studied the effect of WSF on pupil-per-teacher ratio, graduation rates, pseudo-graduation rates, and dropout rates.

Although overall WSF has limited impact on these educational attainments or produces inconclusive results, I discover WSF has no apparent negative effect and must be further studied. First, the mostly null effects of WSF indicate that WSF appears to not harm students from privileged backgrounds which was one of the only policy concerns. This study also emphasizes that researchers have barely scraped the surface of thoroughly understanding WSF. As described in Section 7, there are already 2 potential analyses; however, there are even more undiscovered empirical tests that can further the understanding of WSF such as the effect of WSF on college enrollment, primary school attainments, etc. WSF is implemented by some of the largest and most innovative school districts like New York City and Boston. As WSF continues to spread nationally, it is crucial that policymakers and educators take a more practical approach and study WSF to weigh the benefits and drawbacks of this funding policy.

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[7] Jill V. Jeffery Jody N. Polleck. Common core standards and their impact on

standardized test design: A new york case study. *The High School Journal*, pages 1–26, Fall 2017.

[8] Amy Ellen Schwartz Ross Rubenstein and Leanna Stiefel. Rethinking the intradistrict distribution of school inputs to disadvantaged students. 2006.

[9] C. Kirabo Jackson Rucker C. Johnson. Reducing inequality through dynamic complementarity: Evidence from head start and public school spending. *American Economic Journal: Economic Policy*, pages 310–349, 2019.

Figures and Tables

Figure 1: Educational Attainment Trends Over Time

Pupil Per Teacher Ratio Dropout Rate

Pupil to Teacher Ratio for Control and Treated Districts Districts Treated in 2000-2001

60

19

50

16

1995 2000 2005 2010 2015 2020 Time to Treatment (year)

90

Control Treated

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates
in public school districts enrolling more than 15,000 students

80

Graduation Rate

18

Dropout Rate for Control and Treated Districts

Districts Treated in 2002-2003

5.5

15

70

17

2005 2010 2015 2020 Time to Treatment (year)

Pseudo-Graduation Rate
5

10

Control Treated

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

3.5

0

Pseudo-Graduation for Control and Treated Districts
Districts Treated in 2000-2001

1995 2000 2005 2010 Time to Treatment (year)

4.5

4
5

3

1995 2000 2005 2010 Time to Treatment (year)

Control Treated

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates
in public school districts enrolling more than 15,000 students

Graduation Rate for Control and Treated Districts
Districts Treated in 2012-2013

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

Control Treated

Note: Pupil Per Teacher Ratio from 1995-2018 for 144 control districts versus 2 districts treated in 2000-2001 school year. Graduation Rate from 2007-2018 for 138 control districts versus 1 district treated in 2012-2013 school year. Dropout rates were calculated from 1996-2009 for 343 control districts versus 3 dis tricts treated in 2002-2003 school year. Pseudo-Graduation was calculated from 1995-2009 for 272 control districts versus 2 district treated in 2000-2001 school year using $\frac{\text{\# of high school graduates within district}}{\text{total enrollment within the district}} * 100$.
Treated districts were identified using Georgetown Edunomics WSF Report (Roza et. al 2019-Present).

Figure 2

Pupil per Teacher Ratio Regression Coefficients on Lead and Lag Treatment Years

4

2

0

-2

-4

Coefficient

-20 -10 0 10 20 Time to Treatment(years)

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

95% Confidence Intervals Shown

Note: Regression coefficients with confidence intervals on lead and lag years for Pupil per teacher ratio from 1995-2018 for 8 treated districts and 144 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. The graph was created using Appendix Table A1.

10

0

-10

Coefficient

Figure 3

-20

-5 0 5 10 Time to Treatment(years)

Graduation Rate Regression Coefficients on Lead and Lag Treatment Years

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

95% Confidence Intervals Shown

Note: Regression coefficients with confidence intervals on lead and lag years for Graduation Rates from 2007-2018 for 5 treated districts and 272 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference.The graph was created using Appendix Table A2.

Figure 4

Pseudo-Graduation Regression Coefficients on Lead and Lag Treatment Years

3

2

1

0

Coefficient

-1

-10 -5 0 5 10 Time to Treatment(years)

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

95% Confidence Intervals Shown

Note: Regression coefficients with confidence intervals on lead and lag years for Pseudo-Graduation rate:

$$\frac{\#\text{ of high school graduates within district}}{\text{total enrollment within the district}} * 100$$

Pseudo-Graduation was calculated from 1995-2009 for 4 treated districts and 137 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. The graph was created using Appendix Table A3.

Figure 5

Dropout Rate Regression Coefficients on Lead and Lag Treatment Years

20

5

0

-5

-10

Coefficient

-10 -5 0 5 10 Time to Treatment(years)

Source: NCES Selected statistics on enrollment, teachers, dropouts, and graduates in public school districts enrolling more than 15,000 students

95% Confidence Intervals Shown

Note: Regression coefficients with confidence intervals on lead and lag years for Dropout Rates from 1996- 2009 for 9 treated districts and 343 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. The graph was created using Appendix Table A4.

Urbanicity

Suburb

City

City

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City

in the 1993–94 school year, enrolls 36,793 students, has 86 schools, a poverty

U.S. Department of Education report, *Districts' Use of Weighted Student Funding Systems to Increase School*

SF as of 2019 Table 1: Districts Implementing W

Poverty Rate Number of Schools Enrollment Year Adopted State

District Names

24%

86

36,793 1993–94

MN

Minneapolis Public Schools

9%

92

87,793 1994–95

VA County Public Schoolsilliam

Prince W

33%

54

34,227 1999–2000

OH

Cincinnati Public Schools
31%

283

215,627 2000–01

TX

Houston Independent School District
34%

158

75,749 2000–01

I
W

Milwaukee School District

12%

116

58,865 2002–03

CASan Francisco Unified School District

27%

103

37,698 2002–03

MN

St. Paul Public School District

10%

289

181,995 2006–07

HI

Hawaii Department of Education
20%

189

90,235 2007–08

CODenver Public Schools

26%

1,579

981,667 2007–08

NY

York City Public SchoolsNew

9%

53

29,527 2007–08

COPoudre School District

31%

182

83,666 2008–09

MD

Baltimore City Public Schools

2%

89

66,896 2008–09

CO Douglas County School District

8%

22

20,561 2010–11

COFalcon School District 49

28%

120

53,885 2011–12

MABoston Public Schools

17%

164

146,211 2011–12

NCCharlotte-Mecklenburg Schools

33%

65

40,889 2011–12

NJ

Newark Public School District

12%

207

128,936 2012–13

MD

Prince George's County Public Schools

10%

53

39,287 2013–14

CO Adams 12 Five Star Schools

27%

591

387,311 2013–14

IL

City of Chicago School District 299

43%

101

39,410 2013–14

OH

Cleveland Municipal School District

23%

154

85,598 2015–16

TN

Metro Nashville Public Schools

7%

165

86,731 2015–16

CO Jeffco Public Schools

20%

33

13,265 2015–16

NM

Santa Fe Public Schools

41%

67

31,371 2016–17

IN

Indianapolis Public Schools

33%

89

51,500 2018–19

GA Atlanta Public Schools

34%

208

114,487 2018–19

TN

Shelby County Schools

SF system *Note:* Table reads: Minneapolis Public Schools adopted a W rate of 24 percent, and is located in a city·

Sources: Information gathered from

a National Study· Autonomy and Equity:Findings From

Note: Poverty rates are based on the 2016 Census Small Area Income Poverty Estimate (SAIPE) data for school districts·

Table 2: Summary Statistics

	Sum	Mean	SD	Min	Max	N
Pupil per Teacher 1995-2018						
Control	58,880	17.05	3.12	9	57	3,456
Treated	3,242	16.88	1.87	12	22	192
Total	62,121	17.04	3.07	9	57	3,648
Pseudo-Graduation Rate 1995-2009						
Control	10,172	4.93	0.95	0	9	2,070
Treated	258	4.29	1.23	2	7	60
Total	10,429	4.91	0.97	0	9	2,130
Graduation Rate 2007-2018						
Control	258,454	79.09	11.76	35	100	3,264
Treated	4,110	68.51	9.72	37	83	60
Total	262,564	78.90	11.81	35	100	3,324
Dropout Rate 1996-2009						
Control	23,768	4.95	3.49	0	33	4,802
Treated	689	8.20	3.96	1	21	84
Total	24,457	5.01	3.53	0	33	4,886

Note: Description: Pupil per teacher ratio from 1995-2018 for 8 treated districts and 144 control districts. Pseudo-Graduation Rate which is $\frac{\text{\# of high school graduates within district}}{\text{total enrollment within the district}}$. Pseudo-Graduation was calculated from 1995-2009 for 4 treated districts and 138 control districts. Graduation Rates in percentage form from 2007-2018 for 5 treated districts and 272 control districts. Dropout rates from 1996-2009 for 9 treated districts and 343 control districts. Treated districts were identified using Georgetown Edunomics WSF Report (Roza et. al 2019-Present) and U.S. Department of Education WSF Report (Levin, Manship, Hurlburt, and Atchison 2019).

Table 3: Static Regression Coefficients

	Pupil Per Teacher	Graduation	Pseudo-Graduation	Dropout
Coefficient	0.0414	0.166	0.296	-1.004
	(0.18)	(1.52)	(0.17)	(0.57)
	[0.26]	[0.11]	[1.76]	[-1.78]
Mean Pre-Treatment	16.65	62.89	4.32	9.14
Observations	3,648	3,324	2,130	4,886

Note: Standard errors in parentheses and t-statistics in brackets. Static regression coefficients for every educational attainment. Note that pseudo-graduation is $\frac{\text{\# of high school graduates within district}}{\text{total enrollment within the district}} * 100$.Table of β coefficients Based on Equation 2. Each regression covers unique set of years and has its own set of control and treated schools based on which districts have data: Pupil per teacher ratio from 1995-2018 for 8 treated districts, Graduation Rates from 2007-2018 for 5 treated districts, Pseudo-Graduation from 1995-2009 for 4 treated districts, and Dropout Rates from 1996-2009 for 9 treated districts.

Appendix

Appendix Tables

Table A1: Leading and Lagging Coefficients for Pupil Per Teacher Ratio Dynamic Regression

	(1)
lead/lag year=-21	1.768
	Coefficient
lead/lag year=-20	-0.212
	(1.47)
lead/lag year=-19	1.253
	(1.47)
lead/lag year=-18	-0.0495
	(1.47)
lead/lag year=-17	0.685
	(1.47)
lead/lag year=-16	0.354
	(1.09)
lead/lag year=-15	0.545
	(0.93)
lead/lag year=-14	-0.0487
	(0.93)
lead/lag year=-13	-0.648
	(0.93)
lead/lag year=-12	-0.0144
	(0.77)
lead/lag year=-11	0.220
	(0.69)
lead/lag year=-10	0.0362
	(0.69)
lead/lag year=-9	0.275
	(0.69)
lead/lag year=-8	-0.136
	(0.69)
lead/lag year=-7	-0.0745
	(0.69)
lead/lag year=-6	-0.885
	(0.67)
lead/lag year=-5	-1.264*
	(0.67)
lead/lag year=-4	-0.642
	(0.64)
lead/lag year=-3	-0.432
	(0.65)
lead/lag year=-2	-0.307
	(0.65)
lead/lag year=-1	0
	(0.64)
lead/lag year=0	0.0511
	(.)
lead/lag year=1	-0.281
	(0.64)
lead/lag year=2	-0.0913
	(0.65)
lead/lag year=3	-0.120
	(0.65)
lead/lag year=4	-0.0774
	(0.67)
lead/lag year=5	-0.374
	(0.67)
lead/lag year=6	-0.381
	(0.67)
lead/lag year=7	-0.464
	(0.67)
lead/lag year=8	-0.0997
	(0.69)
lead/lag year=9	-0.323
	(0.73)
lead/lag year=10	-0.569
	(0.73)
lead/lag year=11	-0.378
	(0.73)
lead/lag year=12	1.426
	(0.83)
lead/lag year=13	0.824
	(1.09)
lead/lag year=14	1.675
	(1.09)
lead/lag year=15	-1.362
	(1.09)
lead/lag year=16	-0.881
	(1.09)
lead/lag year=17	0.267
	(1.09)
lead/lag year=18	-0.621
	(1.47)

Constant	17.01***
	(1.47)
Observations	~~3648~~
	(0.63)

~~Standard errors in parentheses~~

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Raw regression coefficients with standard errors on lead and lag years for Pupil per teacher ratio from 1995-2018 for 8 treated districts and 144 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. This table was used to create Figure 2.

Table A2: Leading and Lagging Coefficients for Graduation Rate Dynamic Regression (1)

	Coefficient
lead/lag year=-6	-9.674*
	(4.19)
lead/lag year=-5	-8.585*
	(3.63)
lead/lag year=-4	-4.043
	(3.10)
lead/lag year=-3	-4.713
	(3.10)
lead/lag year=-2	1.002
	(3.10)
lead/lag year=-1	0
	(.)
lead/lag year=0	-6.132*
	(3.10)
lead/lag year=1	-3.117
	(3.10)
lead/lag year=2	-4.739
	(3.10)
lead/lag year=3	-4.068
	(3.10)
lead/lag year=4	-1.625
	(3.10)
lead/lag year=5	-2.564
	(3.10)
lead/lag year=6	-5.371
	(3.63)
lead/lag year=7	-5.211
	(4.19)
Constant	84.98***
	(3.07)
Observations	3324

Standard errors in parentheses

$^{*} p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$

Note: Raw regression coefficients and standard errors in parenthesis on lead and lag years for Graduation Rates from 2007-2018 for 5 treated districts and 272 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. These values were used to create Figure 3.

Table A3: Leading and Lagging Coefficients for Pseudo-Graduation Rate Dynamic Regres sion

	(1)
	Coefficient
~~lead/lag year=-12~~	~~0.348~~
	(0.41)
lead/lag year=-11	0.00444
	(0.41)
lead/lag year=-10	0.0655
	(0.41)
lead/lag year=-9	-0.189
	(0.41)
lead/lag year=-8	-0.0631
	(0.41)
lead/lag year=-7	-0.179
	(0.41)
lead/lag year=-6	-0.0200
	(0.41)
lead/lag year=-5	0.123
	(0.36)
lead/lag year=-4	0.245
	(0.33)
lead/lag year=-3	0.135
	(0.33)
lead/lag year=-2	0.204
	(0.33)
lead/lag year=-1	0
	(.)
lead/lag year=0	0.106
	(0.33)
lead/lag year=1	0.0923
	(0.33)
lead/lag year=2	-0.0428
	(0.33)
lead/lag year=3	0.186
	(0.41)
lead/lag year=4	0.318
	(0.41)
lead/lag year=5	0.650
	(0.41)
lead/lag year=6	1.115^{**}
	(0.41)
lead/lag year=7	1.043^{*}
	(0.41)
lead/lag year=8	0.806^{*}
	(0.41)
lead/lag year=9	0.926^{*}
	(0.41)
lead/lag year=10	1.334^{*}
	(0.53)
Constant	4.798^{***}
	(0.32)
Observations	~~2130~~

~~Standard errors in parentheses~~

$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Note: Raw regression coefficients with standard errors on lead and lag years for Pseudo-Graduation rate:

$$\frac{\text{\# of high school graduates within district}}{\text{total enrollment within the district}} * 100$$

Pseudo-Graduation was calculated from 1995-2009 for 4 treated districts and 137 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. This table was used to create Figure 4.

Table A4: Leading and Lagging Coefficients for Dropout Rate Dynamic Regression

	(1)
	Coefficient
~~lead/lag year=-9~~	~~-5.515~~ *
	(2.22)
lead/lag year=-8	-4.321***
	(1.28)
lead/lag year=-7	-5.227***
	(1.42)
lead/lag year=-6	-1.684
	(1.45)
lead/lag year=-5	2.922*
	(1.41)
lead/lag year=-4	2.824*
	(1.41)
lead/lag year=-3	1.163
	(1.27)
lead/lag year=-2	-1.068
	(1.06)
lead/lag year=-1	0
	(.)
lead/lag year=0	0.240
	(1.07)
lead/lag year=1	-0.792
	(1.03)
lead/lag year=2	-1.810
	(1.08)
lead/lag year=3	-1.488
	(1.16)
lead/lag year=4	-1.667
	(1.34)
lead/lag year=5	-1.642
	(1.49)
lead/lag year=6	-1.472
	(1.34)
lead/lag year=7	-2.260
	(1.45)
lead/lag year=8	-1.839
	(1.45)
lead/lag year=9	-3.231*
	(1.45)
lead/lag year=10	-2.431
	(2.22)
Constant	4.806***
	(1.07)
Observations	~~4886~~

Standard errors in parentheses

$^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

Note: Raw regression coefficients with standard errors on lead and lag years for Dropout Rates from 1996- 2009 for 9 treated districts and 343 control districts. Note the year before treatment has been omitted to avoid multicollinearity and have a relative time reference. This table was used to create Figure 5.

Response to the Referees

I thank the reviewers for their critical assessment of my work. In the following I address their concerns point by point.

Main

Reviewer Point P 0.1 — Main comment: WSF ought to operate more positively on specific groups (students from low-income backgrounds, special needs, ESL) and perhaps negatively on those not in the named groups. Is there any way you could find informa tion by group type? Are there any surveys you could use for which you could aggregate information across districts on different demographic groups to estimate treatment effect heterogeneity? Could you use any of the data from the Equality of Opportunity project as outcomes (http://www.equality-of-opportunity.org/data/)? If you cannot gather appropri ate data in time (entirely fine), could you describe what type of data you would need to gather and what analyses you would implement if you could?

Reply: Between the first draft and final revision, I had very limited time to execute additional data cleaning and analyses. Thus, I created a Future Work section (Section 7) to outline in detail the existing data I would use to understand WSF's effect at the level of specific groups. I also reference empirical methods from my paper to emphasize the versatility of my methods. I also address why I did not prioritize these data sets and methods which reveals the drawbacks of the future analyses.

Reviewer Point P 0.2 — “Over the last two decades, many large school districts across the United States have shifted away from deploying federal funds to districts [schools?] based on uniform staffing formulas to allocating funds to schools within the district based on the particular mix of students within a school.”

Reply: Adjusted wording to school.

Reviewer Point P 0.3 — Move paragraph “Some earlier studies.. ” to after your de scription of what you do and what you find. Also, is there a better topic sentence for that paragraph that perhaps summarizes the literature and your contribution relative to it?

Reply: I adjusted paragraph order and changed topic sentence to summarize what the literature contributes and its limitations on pages 2-3.

Reviewer Point P 0.4 — Expand on sentence “Ultimately this paper finds minute positive but mostly insignificant effects of WSF on graduation rates and pupil-per teacher ratio and inconclusive negative effects on dropout rates.” and turn it into a paragraph.

Reply: Added new paragraph in Introduction on page 2 describing results in more detail, giving quantitative results revealing size, sign, and signficance.

Reviewer Point P 0.5 — Generally try to work on creating succinct topic sentences throughout the paper. For example, “The results of the static regression are found in Table 3 in the Appendix. ” is not a very effective topic sentence. Instead, it could be something like “The static regression reveals positive alas only marginally significant effects on pupil-per teacher ratios, actual and pseudo-graduation rates, and harder-to-interpret negative effects on dropout rates. Table 3 shows . . . ” -

Reply: Read through every topic sentence and made sure every sentence aligned with the infor mation communicated in the paragraph. Edited the topic sentences to summarize and roadmap the paragraph rather than just begin the paragraph.

Reviewer Point P 0.6 — Please organize the tables and figures separately (by figure /table, then by order in which they appear in the paper)

Reply: Separated tables and figures in Appendix. More difficult to order since some figures are referred to at the same time or referred to multiple times. Tried best to organize by order in paper, but also considered numbering figures to coordinate with associated table.

Minor

Reviewer Point P 0.7 — Perhaps Table 4 could go into an Appendix given that you already have Figure 1? (same with the subsequent figures/tables)

Reply: Created separate sections for figures/tables and appendix tables. Appendix Tables now include all the tables of raw coefficients.

Reviewer Point P 0.8 — Define pseudo-graduation rates in each table/figure note where you use it

Reply: Defined pseudo-graduation in every table and figure where there is any result for the pseudo-graduation rate. Also, defined pseudo-graduation in the introduction.

Reviewer Point P 0.9 — You mention figure 5 but there's no figure 5? if you are referring to Figure 6, "Figure 5 in the Appendix demonstrates the presence of parallel trends for each educational attainment for districts treated in various years" → the figure is showing raw data, and it looks like trends are not diverging, but it doesn't demonstrate anything. You "demonstrate" the absence of parallel trends in the pre-period in a statistical sense through the coefficients on the pre-period dummies being statistically indistinguishable from 0 in figures 1-4

Reply: Renamed Figure 6 to Figure 1, changed numbering of other figures, and changed how Figure 1 (previously Figure 6) is referred to throughout the paper. Also, changed how Figure 1 is incorporated into the paper from using the figure to improperly support parallel trends to using it as a visual to show summary statistics and foreshadow the paper's findings.

Reviewer Point P 0.10 — In table 3 you can add info such as which years you are covering and how many treated schools you have for each estimate

Reply: Added information on covered years and number of treated districts for every educational attainment.