ABSTRACT

Estimated Effects of Breakfast in the Classroom on Academic Performance and Human Capital Outcomes

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There has been a movement in recent years within school districts to provide all students with breakfast in classrooms across the United States. In this quasi-experimental study, I investigated the effects of serving breakfast in the classroom on student achievement, attendance, tardiness, retention, and gifted and talented classifications. I used propensity score matching to find that providing students with breakfast in the classroom decreased tardiness and decreased math and reading achievement for fourth graders. Retention rates and gifted and talented classifications increased for fifth graders. Although propensity score matching attempts to control for negative selection present in data, persistence and unobserved characteristics unaccounted for in the model could have impacted the results. Given the consistent negative causal estimates across modeling strategies, policy makers should use caution when supporting the BIC program. There are currently too many unknowns about BIC's effect on students' human capital outcomes to uncritically back its adoption.

Estimated Effects of Breakfast in the Classroom on Academic Performance and Human Capital Outcomes

by

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A Thesis

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CHAPTER ONE

Introduction

1.1 Breakfast in the Classroom

Breakfast is considered the most important meal of the day by nutritionists. However an estimated 12 to 35 percent of children skip breakfast across the United States (Gardner, 2008) causing them to miss out on important cognitive and educational benefits (Wesnes, Pincock, Richardson, Helm, & Hails, 2003). High populations of economically disadvantaged students combined with low school breakfast participation rates have caused decision makers to believe many students are not receiving the nutritional benefits of a balanced breakfast.

Although breakfast is available in the cafeteria for students in the morning, there are multiple reasons for low participation rates observed in school based breakfast. In order to participate, students must arrive early which can be difficult for those who walk or take the bus to school. There is also a stigma associated with school breakfast and low-income students. Students may not feel comfortable going to the cafeteria to eat breakfast because they are aware of the reputation behind the need to eat breakfast at school.

Because breakfast has been shown to improve cognitive performance, and there are low breakfast participation rates nation wide, a program called Breakfast in the Classroom (BIC) has been implemented in school districts across the nation. BIC provides all students regardless of economic background the opportunity to consume a USDA approved, nutritious meal in the students' classroom at the time school begins. This improves the quality of the students' mornings by removing the need for students to arrive early in order to consume breakfast. The stigma associated with consuming breakfast at school is also eliminated since all students are provided

the same opportunity. Potential disadvantages of the BIC program include students ultimately consuming twice the number of calories they normally would have by eating breakfast at home and at school. Additionally, the time it takes to serve the breakfast could negatively impact instructional time for teachers, though this does not seem to be an issue according to surveys.

1.2 Dallas ISD

In this study, I explored the effect of the BIC program implemented in 2011 in Dallas ISD on elementary schools' student achievement, attendance, tardiness, retention, and gifted and talented classifications as compared to schools who continued to provide the traditional breakfast in the cafeteria. The pilot began in the fall of 2010 with 14 elementary and middle schools before adding 49 elementary schools by May 2013. In order to qualify for the pilot, at least 80 percent of the schools' student population had to be eligible for free or reduced-price lunch. Students are considered eligible for free lunch if their families earn up to 130 percent of the poverty line and reduced-price lunch if their families earn up to 185 percent of the poverty line. Of the approximately 157,000 students that attended DISD in 2011, 89 percent of those students were eligible for free or reduced lunch, yet breakfast participation district wide was approximately 30 percent (*Breakfast in the Classroom: A Case Study*, 2013). However, not all schools with such populations applied for the program. Many "low resource" schools did not want to risk losing instructional time to the program, whereas "high resource" schools did not feel the program was necessary for their campus' needs.

The DISD BIC pilot data spans from 2008 to 2013 and examines elementary schools that implemented the BIC pilot program in the 2011-2012 academic year. I investigated the impact of the program on student achievement, attendance, tardiness, retention, and gifted and talented classification. I found that providing students

breakfast in the classroom decreased tardiness and math and reading scores while having no effect on math and reading passing rates. I attributed this to the overall small decrease that occursed in math and reading scores and realized that it is not enough to impact the passing threshold. Fifth graders experienced increases in retention rates and gifted and talented classifications. Because of the manner in which schools participated, I suggest that negative selection is present within the study. Though the methods controlled for much of the negative selection, unobserved characteristics that are not accounted for in the model could have affected the results. Policy makers should be cautious of supporting the BIC program while how it affects student outcomes is still to be discovered.

CHAPTER TWO

Background

2.1 Review of Prior BIC Literature

There is evidence that children who consume breakfast are more likely to increase attention or cognitive function (Mahoney, Taylor, Kanarek, & Samuel, 2005; Wesnes et al., 2003). Most studies focusing on nutritional programs concentrated on nonacademic outcomes such as nutrient intake (Friedman & Hurd-Crixell, 1999; Gordon et al., 2007) and food insecurity (Bernstein, Crepinsek, McLaughlin, & Singh, 2006; Wojicki & Heyman, 2006).

Studies that used natural experiments to find the effect school food programs have on student outcomes typically yielded positive results. Leos-Urbel, Schawartz, Weinsetien, and Corcoran (1999) studied the universal breakfast program implemented in New York City and found an increase in participation and attendance for blacks and Asians. Bernstein et al. (2006) however found little evidence of BIC improvement on achievement, attendance, and discipline. The study was considered randomized, yet principals were allowed to decide whether to have breakfast in the classroom or in the cafeteria, causing biased estimations.

Imberman and Kugler (2014) conducted a nonexperimental analysis of differential timing for a breakfast program that found increased math and reading scores and even higher outcomes for low performing and free-lunch students. However, due to how the program was implemented and the results of the analysis, it was suggested that breakfast in the classroom impacted test taking rather than actual learning. Schanzenbach (2009) used experiemental data on providing breakfast in the classroom and found take-up rates increased, but very little increases in health, behavior, and achievement.

A study was previously done on the same data that was used in my study by the Texas Hunger Initiative (Krey & Nolen, 2013). They found by running t-tests, chi-squared tests, and ANOVAs on a smaller sample that tardies declined and math and reading scores increased. In my quasi-experimental study, all schools in the dataset were eligible to participate in the program. The principals of schools ultimately decided whether or not to participate. The effects were estimated using a propensity score matching strategy. I theorized that BIC will impact student achievement, attendance, tardiness, retention, gifted and talented classifications.

2.2 Hypothesized Selection Bias

I was interested in estimating the causal effect of BIC on observed student outcomes in the year following the intervention. The fundamental problem of causal inference is that causality is unobservable at the individual level due to the lack of data on student counterfactuals. Thus, causal analysis in the potential outcomes framework relies on credible identifying assumptions that apply to groups of individuals. This can be seen in the following decomposition of a simple difference in means (Morgan & Winship, 2007). Without counterfactuals, causal analysis of a policy requires comparing a particular group of units' outcome, y, exposed to BIC, $d_i = 1$, to unexposed units, $d_i = 0$:

$$E_N[y_i|d_i = 1] - E_N[y_i|d_i = 0] \tag{2.1}$$

where the first term in the difference is the sample average outcome for the BIC treatment group and the second term is the sample average for the control group. This difference in sample averages is sometimes called the "simple difference in means operator" (Angrist & Pischke, 2009) or the "naive average treatment effect estimator" (Morgan & Winship, 2007). Using algebra, definitions of key terms and some manipulation, we can decompose this simple difference in means into the true average

treatment effect plus various sources of bias. We do that now so as to highlight the assumptions necessary for identifying the true causal effect of BIC on student outcomes.

First, we define some terms. The average treatment effect (ATE), average treatment effect on the treatment group (ATT) and the average treatment effect on the untreated group (ATU) are equal to, respectively:

$$\begin{aligned} \text{ATE} &= E[Y^1] - E[Y^0] && (2.2) \\ \text{ATT} &= E[Y^1|D=1] - E[Y^0|D=1] && (2.3) \\ \text{ATU} &= E[Y^1|D=0] - E[Y^0|D=0] && (2.4) \end{aligned}$$

where $E[\dot{]}$ is the expectation operator, Y^1 and Y^0 are potential outcomes and D is an indicator variable equalling 1 if the population of units receive the treatment and 0 otherwise. Note, that a difference in expectation is equal by definition to the sum of weighted conditional average expectations, we can rewrite the ATE equation:

$$\begin{aligned} \text{ATE} &= E[Y^1] - E[Y^0] && (2.5) \\ &= \pi E[Y^1|D=1] + (1-\pi)E[Y^1|D=0] \\ &\quad -\pi E[Y^0|D=1] + (1-\pi)E[Y^0|D=0] && (2.6) \end{aligned}$$

I will now use simplified notation. Let $E[Y^1|D=1] = a$, $E[Y^1|D=0] = b$, $E[Y^0|D=1] = c$, $E[Y^0|D=0] = d$ and ATE $= e$. I then rewrite using this simplified notation the definition of ATE:

$$e = \{\pi a + (1-\pi)b\} - \{\pi c + (1-\pi)d\} \quad (2.7)$$

Next I make the following substitutions so as to isolate the simple difference in means on the left-hand side of this identity:

$$\begin{aligned} e &= \{\pi a + (1-\pi)b\} - \{\pi c + (1-\pi)d\} \\ \mathbf{a-d} &= e + (\mathbf{c-d}) + (1-\pi)(a-c) - (1-\pi)(b-d) \end{aligned}$$

The left-hand-side term, $a-d$ is equal to the simple difference in means operator. To reveal this, I substitute the conditional means for all of the terms now:

$$\begin{aligned}
E[Y^1|D=1]-E[Y^0|D=0] &= \text{ATE} \\
&\quad +(E[Y^0|D=1]-E[Y^0|D=0]) \\
&\quad +(1-\pi)(\{E[Y^1|D=1]-E[Y^0|D=1]\} \\
&\quad -(1-\pi)\{E[Y^1|D=0]-E[Y^0|D=0]\}) \\
E[Y^1|D=1]-E[Y^0|D=0] &= ATE \\
&\quad +(E[Y^0|D=1]-E[Y^0|D=0]) \\
&\quad +(1-\pi)(ATT-ATU)
\end{aligned}$$

In conclusion, the simple difference in means can be decomposed into the following three components:

$$\begin{aligned}
\underbrace{E_N[y_i|d_i=1]-E_N[y_i|d_i=0]}_{\text{SDM}} &= \underbrace{E[Y^1]-E[Y^0]}_{\text{Average Treatment Effect}} \\
&\quad + \underbrace{E[Y^0|D=1]-E[Y^0|D=0]}_{\text{Selection bias}} \\
&\quad + \underbrace{(1-\pi)(ATT-ATU)}_{\text{Heterogenous treatment effect bias}}
\end{aligned}$$

The left-hand-side term, SDM, is the simple difference in means calculated using sample averages. The elements on the right-hand-side are the definition of the simple difference in means rearranged according to some basic assumptions. Those assumptions are: $E_N[y_i|d_i=1] \rightarrow E[Y^1|D=1]$, $E_N[y_i|d_i=0] \rightarrow E[Y^0|D=0]$ and $(1-\pi)$ is the share of the population in the control group.

If BIC was randomly assigned to schools, then I could effectively eliminate some of the terms on the right-hand-side. However, because school officials were able to choose whether or not to participate, there are suspicions of negative selection. If I were to calculate the propensity score or probability of a student being assigned breakfast in the classroom given a set of observed covariates, I could then match

students based on similar propensity scores using the nearest neighbors with replacement method. This would allow me to mimic randomization by creating a sample of students that received the treatment that is comparable on all observed covariates to a sample of students that did not receive the treatment, therefore eliminating the selection bias portion of the right hand side.

CHAPTER THREE

Methodology

3.1 BIC Background

The DISD BIC program provided children of all socioeconomic backgrounds with a free breakfast at the beginning of each school day in the students' classrooms. Alternatively, in non-BIC schools, students were able to arrive at the cafeteria before school began and pay for breakfast based on their eligibility level. BIC allowed children to eat breakfast after the school day had begun in their classrooms while teachers took attendance, checked homework, and prepared for the day. The program permited students to go directly to class when they arrived at school and gave them an opportunity to consume a nutritious breakfast they otherwise might not have had. By providing breakfast in this manner, the stigma of only low-income children consuming school breakfast was eliminated. However, the program also gave some students the opportunity to eat breakfast twice, increasing the child's total caloric consumption.

The way breakfast was delivered to the students in BIC schools differed depending on the needs of the school. There were three methods that the principals were able to choose from. The first method was the hallway kiosk which was a station assembled in the hallway each morning. Students were able to pick up a packed breakfast from the kiosk on their way to their classroom once the bell rang. The second was the grab and go method, in which students stopped by the cafeteria on the way to their classroom and picked up a packed breakfast to eat in the classroom. The final method was for the breakfast to be directly delivered to the classroom. Breakfasts were packaged and delivered in insulated carriers to the classroom once the bell rang.

Our data did not contain which method was used in each of the BIC schools, which could affect the results of the study.

The pilot began in the fall of 2010 with 14 elementary and middle schools. In order to qualify for the program, 80 percent of the school's population had to be considered economically disadvantaged. School officials were able to choose whether or not to participate, and not all schools that qualified chose to participate. All schools in the dataset were eligible to participate, therefore the reasons why some chose to participate and others not were viewed as unobservable characterics. For this reason, I identified the treatment effects initially with OLS regressions, followed by a propensity score matching method.

3.2 Data Description

The data used in this study consisted of DISD student records. The majority of schools that participated in the pilot were elementary schools, therefore only elementary schools are used in this study. The years of data available ranged from 2008 to 2012. Because state assessment testing begins in third grade, the data consisted of grades three through five. The achievement data used in the analysis was from the state assessment in math and reading. This exam is the deciding factor in whether or not the student can advance to the following grade, and is also how the Texas Education Agency (TEA) measures school progress. Students are permitted to retake the exam, however the data only had one grade per student per year in our dataset. Therefore it is thought to be the most recent test taken by the student. Math and reading scale scores had over 10,000 missing observations for the academic years 2009-2010 and 2010-2011, and therefore were not able to be used in the analysis.

The state of Texas changed the state assessment from TAKS to STAAR in 2011-2012, the same year that BIC was implemented. STAAR is known to be more rigorous, test critical thinking, and have different acceptable passing rates than the

TAKS test. However, because all schools in the sample experienced the same change, BIC was still the only observed difference between BIC and non-BIC schools.

Along with passing rates, the data offered other student outcome variables. Attendance rates were created by taking the number of days attended and dividing it by the number of days enrolled for each student. There was information on whether or not the student had been retained or held back the previous year and whether or not the student was classified as gifted and talented. The data also provided information on student demographis such as race, gender, language proficiency, and economic status. School level characteristics were created by taking the mean of the observtions for each school by year. Table 3.1 reflects the summary statistics for the entire sample, BIC schools, and non-BIC schools.

The table includes data from the 2010-2011 academic year. School characteristics across both control and treatment groups were relatively similar. Both control and treatment groups had high minority populations, with a Hispanic population of 69 percent in the treated schools. Both schools had high economically disadvantaged populations, though BIC schools had a slightly higher population than their counterparts by 5 percent. I analyzed t-tests comparing the schools that participated to those that did not and found that only free lunch and reading pass variables were significant at the 10 percent confidence interval. The characteristics of both groups were similar making the experiment quasi-random.

There were 10,221 students in the OLS estimations for fourth graders and 10,676 students in the OLS estimations for fifth graders. Academic years 2010-2011 and 2011-2012 were used due to the low number of observations for some of the pretreatment outcome variables in the 2009-2010 school year.

The propensity score matching sample contained 7,997 fourth grade observations of each of the outcome variables for the years 2009-2010 through 2011-2012 and 7,349 fifth grade observations of each of the outcome variables for the years 2008-

2010 through 2011-2012. I matched individual students based on a propensity score or probability of a student being assigned breakfast in the classroom based on a given set of covariates. The covariates differed depending on the grade of the student given the differing amount of data available for each grade level. Fourth graders' covariates included 2009 and 2010 historic school characteristics, as well as 2010 individual characteristics, and demographic information, while fifth graders' covariates consisted of 2008 through 2010 historic school characteristics, 2009 and 2010 individual characteristics and demographic information.

3.3 Method

To begin estimating the effects of BIC on student outcomes, we first estimated the effect of BIC using OLS,

$$Y_{i,s} = \alpha + \delta BIC_s + \gamma_1 X_{1,i} + \gamma_2 X_{2,i,\tau} + \Psi S_{s,\tau} + \varepsilon_{i,s} \tag{3.1}$$

where $Y_{i,s}$ is student test scores, passing rates, retention rates, tardiness rates or absenteeism for student i in school s for the year 2011-2012. We controlled for time-invariant individual characteristics such as race and gender ($X_{1,i}$), time-variant individual characteristics such as lagged absentees and lagged free lunch characteristics ($X_{2,i,\tau}$), and lagged school level characteristics such as the school averages for each school by year, such as the share that was black or the share that passed math test scores ($S_{s,\tau}$). The treatment variable, BIC, varied at the school level, not the individual level.

In order to test the validity and spuriousness of the OLS results, I ran placebo tests by regressing BIC's effect on exogenous covariates such as race/ethnicity, historic socioeconomic variables, gifted and talented classifications, and historic outcome variables.

Due to the results of the placebo tests, I estimated the effects using a propensity score matching strategy. The propensity score is defined as the selection probability of treatment conditional on the confounding variables:

$$p(X) = Pr(D = 1|X). \tag{3.2}$$

This method has two identifying assumptions. Rosenbaum and Rubin (1983) call the first identifying assumption the *conditional independence assumption*. Formally, this assumption is:

$$(Y_i^0, Y_i^1) \perp\!\!\!\perp D|X_i. \tag{3.3}$$

This equation stipulates that there exists a set of X *observable* covariates such that after controlling for these covariates, treatment assignment is independent of potential outcomes, or "as good as random."

The second identifying assumption is called the *common support* assumption. For each value of X, there is a positive probability of being both treated and untreated

$$0 < Pr(D_i = 1|X_i) < 1. \tag{3.4}$$

This condition ensures that the probability of treatment for every value of the vector X is strictly within the unit interval, as is the probability of not receiving treatment. Common support ensures there is sufficient overlap in the characteristics of treatment and control units to find adequate matches.

Table 3.1: Summary Statistics for 2010-2011

VARIABLES	(1) Full Sample mean (sd)	(2) Non-BIC Control Group mean (sd)	(3) BIC Treatment Group mean (sd)
Chronically Absent	3.443	3.305	3.751
	(2.560)	(2.683)	(2.256)
At Risk Absent	13.54	13.40	13.85
	(4.553)	(4.617)	(4.437)
No Risk Absent	83.02	83.30	82.40
	(6.410)	(6.487)	(6.260)
Percent Absent	0.0275	0.0271	0.0283
	(0.00687)	(0.00696)	(0.00666)
Exited Lang Prof	0.142	0.148	0.129
	(0.481)	(0.523)	(0.372)
Limited Lang Prof	47.32	46.28	49.63
	(22.45)	(23.26)	(20.57)
Oneway Lang Prof	0.242	0.225	0.279
	(0.607)	(0.630)	(0.555)
Twoway Lang Prof	0.273	0.346	0.109
	(1.530)	(1.798)	(0.579)
Proficient Lang Prof	52.03	53.00	49.85
	(22.64)	(23.49)	(20.70)
Free Lunch	87.01	85.43	90.56
	(14.13)	(16.11)	(7.062)
Reduced Lunch	4.477	4.669	4.049
	(2.443)	(2.465)	(2.363)
Full Price Lunch	8.510	9.904	5.394
	(13.41)	(15.52)	(5.583)
Math Pass	85.22	86.01	83.46
	(7.673)	(7.735)	(7.306)
Reading Pass	85.88	86.61	84.26
	(6.462)	(6.378)	(6.419)
Retained	2.362	2.278	2.548
	(2.298)	(2.425)	(1.997)
Special Ed	7.459	7.334	7.739
	(3.798)	(4.052)	(3.180)
Gifted and Talented	11.48	11.85	10.65
	(6.224)	(6.779)	(4.719)
Male	51.22	51.19	51.27
	(5.760)	(6.543)	(3.482)
Black	27.02	26.93	27.23
	(28.70)	(28.88)	(28.62)
Hispanic	67.74	66.85	69.73
	(28.70)	(29.06)	(28.06)
White	4.148	4.942	2.373
	(10.54)	(11.96)	(6.054)
Other	1.086	1.274	0.666
	(2.173)	(2.511)	(0.990)
Observations	152	105	47

CHAPTER FOUR

Results

4.1 OLS Estimates

The original estimates, which can be found in Appendix A, simply examined differences in outcomes between students who attended BIC schools and those who did not and gradually controlled for observable charateristics. Table 4.1 displays the results after controlling for demographics, individual characteristics, and historic school characteristics. Fourth grade BIC students were more likely to fail the math assessment at a 10 percent confidence interval but less likely to be retained and absent at the 5 percent confidence interval. Students were less likely to be absent at a 5 percent confidence interval and less likely to be tardy at a 10 percent confidence interval. There were negative effects on reading assessment scores at the 5 percent confidence interval and on math assessment scores at the 1 percent confidence interval. Fifth grade BIC students were more likely to be retained at a 10 percent confidence interval and made lower scores on the reading assessment at a 5 percent confidence interval.

4.2 Placebo Estimates

In order to check for spurious results, I ran placebo tests by regressing the BIC effect on exogenous covariates that should not be affected by something like the treatment. Table 4.2 shows that the treatment effect of providing breakfast in the classroom in 2011 results in highly significant effects. Fourth grade students in 2011 were less likely to be white, and the chances of them passing the math and reading assessments in 2010 were less likely. Fourth grade students were also less likely to be classified in 2010 as gifted and talented, more likely to be eligible for free lunch, and

less likely to qualify for full price lunch. Fifth graders were less likely to be white, more likely to black, more likely to be eligible for free lunch and less likely to qualify to be classified as full price lunch, all at 1 percent confidence levels.

4.3 Propensity Score Matching Estimates

Because of these results, another strategy had to be implemented in order to test the validity of the effect of BIC on student outcomes. Columns 1 and 3 of Table 4.3 describe the estimated causal effects of breakfast in the classroom on the listed outcomes using estimated propensity scores before the population was trimmed to contain only overlapping observations. Figure 4.1 shows the overlap that occurs when propensity scores are estimated for fourth graders based on their given covariates. Columns 2 and 4 of Table 4.3 describe the estimated causal effects after the sample has been trimmed of students with propensity scores that are not contained in the overlap. This removes students at the extremes of the propensity score distributions, essentially controlling the negative selection present in the data.

The estimated causal effects before trimming for fourth graders showed a 0.4 percent decrease in absences at a 10 percent confidence interval and a 0.3 percent decrease in tardies at a 5 percent confidence interval. However once trimming occured and negative selection was controlled for, these effects became smaller or even nonexistent. The effect on absences was eliminated and the effect on tardies decreased to a 0.2 percent decrease at a 10 percent confidence interval. In the trimmed sample, I found that students provided breakfast in the classroom scored 37 points lower on the math portion of the state assessment at a 10 percent confidence interval. One question on the state assessment is worth approximately 30 points. Therefore fourth grade BIC students missed 1 more question than their counterparts. It is not surprising that significant effects are not found for passing rates just because effects were found for overall math grades. Because of the relative small size of the effect,

it would seem that a large effect would be neccesary to cross the failing threshold of the passing rate variable.

Fifth graders' estimated effects before trimming demonstrated that students provided with breakfast in the classroom were approximately 8 percent less likely to pass the math assessment and were roughly 4 percent more likely to be classified as gifted and talented at a 1 percent confidence interval. Fifth grade BIC students made approximately 165 points lower than their counterparts on both reading and math assessments and were roughly 4 percent less likely to pass the reading test at the 10 percent confidence interval. Once the sample was trimmed, significant effects were eliminated except for retention rates and gifted and talented classifications. Fifth grade BIC students were approximately 1 percent more likely to be retained and 3 times more likely to be classified gifted and talented at the 5 percent confidence interval.

Table 4.1: OLS estimates of Breakfast in the Classroom's effect on student outcomes

Outcomes	Fourth graders	Fifth graders
Passed Math (STAAR 2011)	-0.0173*	-0.00373
	(0.00983)	(0.00911)
Passed Reading (STAAR 2011)	0.00257	-0.0122
	(0.00923)	(0.00873)
Math grade (STAAR 2011)	-17.06***	-4.699
	(5.649)	(5.647)
Reading grade (STAAR 2011)	-12.45**	-11.79**
	(5.694)	(5.731)
Absences / total enrollment (2011)	-0.00108**	0.000399
	(0.000511)	(0.000512)
Tardies / total enrollment (2011)	-0.00117*	-0.000193
	(0.000633)	(0.000614)
Student retained (2011)	-0.00528**	0.00523*
	(0.00241)	(0.00306)
Student promoted to G&T (2011)	0.00195	0.00442
	(0.00539)	(0.00644)
N	10,221	10,676

This table is interpreted as follows: the first row is the OLS estimate of BIC on the probability a student passed the math section of STAAR; the third row is the propensity score estimate of BIC on the probability a student passed the reading section of STAAR; etc. These models were estimated separately for the fourth and fifth graders. Robust standard errors are in parentheses. Statistical significance is denoted according to the following legend for the reader's convenience: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.2: Placebo estimates of Breakfast in the Classroom's effect on student outcomes

Outcomes	Fourth graders	Fifth graders
Passed Math (TAKS 2010)	-0.0280***	-0.0107
	(0.00816)	(0.00782)
Passed Reading (TAKS 2010)	-0.0164**	-0.0119
	(0.00745)	(0.00815)
White	-0.0151***	-0.0212***
	(0.00375)	(0.00360)
Black	0.0145*	0.0288***
	(0.00871)	(0.00877)
Hispanic	0.00131	-0.000798
	(0.00929)	(0.00927)
Other	-0.000720	-0.00684***
	(0.00233)	(0.00220)
Free Lunch 2010	0.0537***	0.0473***
	(0.00640)	(0.00647)
Reduced Lunch 2010	-0.00107	-0.00578
	(0.00444)	(0.00407)
Full Price Lunch 2010	-0.0526***	-0.0415***
	(0.00486)	(0.00527)
Retained 2010	0.00133	0.000405
	(0.00372)	(0.00248)
Gifted and Talented 2010	-0.0228***	-0.00404
	(0.00591)	(0.00632)
Observations	10,221	10,676

This table is interpreted as follows: the first row is the OLS estimate of BIC on the probability a student passed the math section of STAAR; the third row is the propensity score estimate of BIC on the probability a student passed the reading section of STAAR; etc. These models were estimated separately for the fourth and fifth graders. Robust standard errors are in parentheses. Statistical significance is denoted according to the following legend for the reader's convenience: * p<0.10, ** p<0.05, *** p<0.01.

Table 4.3: Propensity score estimates of Breakfast in the Classroom's effect on student outcomes

	(1)	(2)	(3)	(4)
	Fourth graders		Fifth graders	
Outcomes	Before	After	Before	After
Passed Math (STAAR 2011)	0.0342	0.00365	-0.0780***	-0.0126
	(0.0299)	(0.0196)	(0.0209)	(0.0214)
Passed Reading (STAAR 2011)	0.0132	0.0383	-0.0398*	0.0143
	(0.0285)	(0.0241)	(0.0216)	(0.0208)
Math grade (STAAR 2011)	-48.32	-37.04*	-166.9*	-34.79
	(29.87)	(19.18)	(93.67)	(29.35)
Reading grade (STAAR 2011)	-35.45	-26.93	-164.2*	-38.59
	(25.39)	(16.38)	(91.59)	(29.47)
Absences / total enrollment (2011)	-0.00359*	-0.00181	0.00165	-0.00154
	(0.00185)	(0.00126)	(0.00295)	(0.00141)
Tardies / total enrollment (2011)	-0.00312**	-0.00203*	0.00213	0.000508
	(0.00124)	(0.00105)	(0.00150)	(0.00150)
Student retained (2011)	-0.000903	0.000611	0.00735	0.00944**
	(0.00344)	(0.00414)	(0.00453)	(0.00434)
Student promoted to G&T (2011)	0.0214	0.0106	0.0439***	0.0364**
	(0.0213)	(0.0140)	(0.0166)	(0.0152)
N	10,221	7,997	9,754	7,349

This table is interpreted as follows: the first row is the propensity score estimate of BIC on the probability a student passed the math section of STAAR; the third row is the propensity score estimate of BIC on the probability a student passed the reading section of STAAR; etc. The Before and After columns refer to before and after I trimmed the data to exclude observations that violate overlap condition. Models were estimated for fourth and fifth graders seperately. Standard errors are in parentheses. Statistical significance is denoted according to the following legend for the reader's convenience: * p<0.10, ** p<0.05, *** p<0.01.

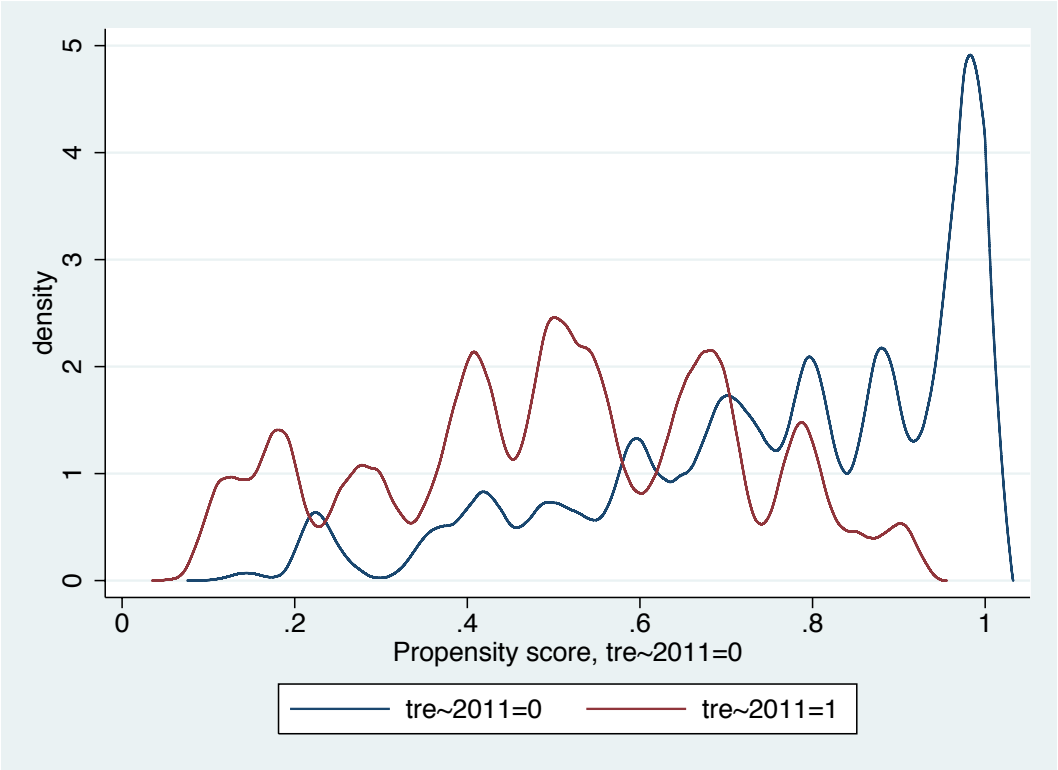

Figure 4.1: Overlap of propensity score for treatment and control groups before trimming

CHAPTER FIVE

Discussion

5.1 Conclusion

Research on the importance of breakfast in the morning for cognitive and nutritional reasons has caused school officials to look into providing free breakfast in the classroom to their students during school hours. With this method, students are able to avoid the stigma of only low income students eating cafeteria breakfast and are able to arrive to school on time. This study examined the impact of providing students with breakfast in the classroom on achievement, attendance, tardiness, retention, and gifted and talented classification. The data used was provided from the DISD piloted BIC program that was implemented in 2010-2011.

Using the propensity score matching method, I found that providing students with breakfast in the classroom caused tardies to decline and decreased math and reading scores on state assessments for fourth graders. Fifth graders experienced an increase in retention rates as well as gifted and talented classifications. Because students were provided with food in the classroom and did not have to eat before school, they were able to get to school on time and therefore decrease the number of tardies. The portion of the right hand side that I was not able to eliminate, the heterogeneous treatment effect bias, could account for the the decline in math and reading scores. It is also possible that students at schools that participated in BIC did not possess the same unobservable test taking skills as their counterparts.

Another possibility is that the findings here are consistent with what took place in DISD. Parents were informed that BIC schools were going to begin providing all students with free breakfast in the classroom. In turn, as the relative price of breakfast decreased, parents decreased the number of breakfasts provided at home as

the number of breakfasts provided at school increased, also known as the substitution effect. An unintended consequence of this could have resulted in an overall decrease in family quality time. Another consequence could have been an overall decrease in calorie intake. Our data did not contain student take-up rates, meaning it is unknown which students did not eat before and who, with the program, began or stopped eating breakfast. Therefore students' parents could have decreased home breakfasts expecting their child to consume school breakfasts. However, the stigma associated with school breakfast could have persisted causing the students to not eat breakfast at school either, leading to an overall decrease in calorie consumption. Both scencarios could contribute to a decline in math scores and other the negative effects seen in this study.

Regression and propensity score matching are only able to uncover causal effects when variables, both observed and unobserved, can be controlled for. The most obvious and available individual and school level characteristics were controlled for in the models presented here based on my own study of the program as well as human capital literature. Through these modeling experiences, the worst case scenario would be that the BIC program harms student performance. In a best case, it has no effect on achievement and decreases the number of tardies. It is also possible that, due to the lack of data, the research design used here did not include all of the factors necessary to determine treatment assignment and outcomes. In that case, negative selection remains an issue that could be solved by designs such as differences-in-differences or instrumental variables which account for problems concerning selection on observables.

5.2 Policy Implications

The policy implication for this study suggests that there is little evidence to support BIC's efficacy for influencing low income student achievement. The consis-

tent negative effects on student achievement found across both modeling strategies suggests that policy makers should use caution when making decisions concerning the effectiveness of BIC. There are simply too many unknowns about BIC's effect on students' human capital outcomes to support its adoption.

APPENDICES

APPENDIX A

OLS Estimates Tables

Table A.1: OLS estimates of Breakfast in the Classroom's effect on Math Passing Rates for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.049***	-0.044***	-0.024**	-0.017*
	(0.011)	(0.010)	(0.009)	(0.010)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.002	0.030	0.204	0.215
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.55	0.55	0.55	0.55

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.2: OLS estimates of Breakfast in the Classroom's effect on Reading Passing Rates for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.032***	-0.028***	-0.006	0.003
	(0.010)	(0.010)	(0.009)	(0.009)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.028	0.253	0.257
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.66	0.66	0.66	0.66

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.3: OLS estimates of Breakfast in the Classroom's effect on Math Scores for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-24.765***	-23.854***	-20.441***	-17.056***
	(5.942)	(5.954)	(5.398)	(5.649)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.002	0.004	0.205	0.210
N	10,221	10,221	10,221	10,221
Mean of dependent variable	1538.54	1538.54	1538.54	1538.54

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.4: OLS estimates of Breakfast in the Classroom's effect on Reading Scores for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-24.758***	-23.541***	-17.620***	-12.455**
	(6.052)	(6.062)	(5.446)	(5.694)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.002	0.008	0.216	0.221
N	10,221	10,221	10,221	10,221
Mean of dependent variable	1522.49	1522.49	1522.49	1522.49

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.5: OLS estimates of Breakfast in the Classroom's effect on Gifted and Talented Rates for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.028***	-0.025***	-0.001	0.002
	(0.008)	(0.008)	(0.005)	(0.005)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.015	0.529	0.533
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.16	0.16	0.16	0.16

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.6: OLS estimates of Breakfast in the Classroom's effect on Retention Rates for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.003	-0.003	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.003	0.079	0.083
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.01	0.01	0.01	0.01

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.7: OLS estimates of Breakfast in the Classroom's effect on Percent Absent for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.000	-0.000	-0.001	-0.001**
	(0.001)	(0.001)	(0.000)	(0.001)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.036	0.452	0.455
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.03	0.03	0.03	0.03

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.8: OLS estimates of Breakfast in the Classroom's effect on Percent Tardy for 4th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.002***	-0.002***	-0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.015	0.251	0.256
N	10,221	10,221	10,221	10,221
Mean of dependent variable	0.01	0.01	0.01	0.01

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.9: OLS estimates of Breakfast in the Classroom's effect on Math Passing Rates for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.023**	-0.016	-0.009	-0.004
	(0.010)	(0.010)	(0.009)	(0.009)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.020	0.260	0.265
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.65	0.65	0.65	0.65

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.10: OLS estimates of Breakfast in the Classroom's effect on Reading Passing Rates for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.032***	-0.027***	-0.019**	-0.012
	(0.010)	(0.010)	(0.008)	(0.009)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.020	0.278	0.282
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.70	0.70	0.70	0.70

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.11: OLS estimates of Breakfast in the Classroom's effect on Math Scores for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-10.493*	-8.380	-9.050*	-4.699
	(6.254)	(6.278)	(5.323)	(5.647)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.005	0.318	0.324
N	10,676	10,676	10,676	10,676
Mean of dependent variable	1596.65	1596.65	1596.65	1596.65

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.12: OLS estimates of Breakfast in the Classroom's effect on Reading Scores for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-16.967***	-15.745**	-16.608***	-11.788**
	(6.394)	(6.408)	(5.382)	(5.731)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.006	0.342	0.346
N	10,676	10,676	10,676	10,676
Mean of dependent variable	1580.48	1580.48	1580.48	1580.48

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.13: OLS estimates of Breakfast in the Classroom's effect on Gifted and Talented Rates for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.013	-0.008	-0.005	0.004
	(0.008)	(0.008)	(0.006)	(0.006)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.013	0.449	0.459
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.20	0.20	0.20	0.20

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.14: OLS estimates of Breakfast in the Classroom's's effect on Retention Rates for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	0.005*	0.005	0.004	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.001	0.087	0.093
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.02	0.02	0.02	0.02

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.15: OLS estimates of Breakfast in the Classroom's effect on Percent Absent for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.000	0.027	0.428	0.432
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.03	0.03	0.03	0.03

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

Table A.16: OLS estimates of Breakfast in the Classroom's effect on Percent Tardy for 5th graders in 2011

Variable names:	1	2	3	4
Breakfast in the classroom school	-0.003***	-0.003***	-0.002***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Demographic controls	No	Yes	Yes	Yes
Lagged individual outcomes	No	No	Yes	Yes
Historic school means	No	No	No	Yes
R-squared	0.001	0.014	0.223	0.232
N	10,676	10,676	10,676	10,676
Mean of dependent variable	0.01	0.01	0.01	0.01

All other control variable coefficients are suppressed for the sake of brevity and available upon request. Heteroskedastic robust standard errors are shown in parenthesis. * p<0.10, ** p<0.05, *** p<0.01

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