University of Arkansas for Medical Sciences

April, 2022

Dear Members of the selection committee and REStat editors,

I am writing to apply for the fellowship support to attend the 2022 NBER Summer Institute. Currently, I am a Post Doctoral Fellow in the Center for the Study of Obesity at the University of Arkansas for Medical Sciences. I am originally from Colombia and earned my Ph.D. in Economics from the University of Arkansas in 2017.

My research focuses on four sub-fields of applied microeconomics that host a meeting during the third week of the 2022 Summer Institute: Health Economics (July 25), Public Economics (July 26-27), Education (July 27), Economics of Children (July 28-29). I have published in *The American Journal of Agricultural Economics*, *Economics of Education Review*, *Economic Development and Cultural Change*, and *World Development*.

Thank you in advance for considering my application, and I appreciate the effort and time it will take to review my documents. I look forward to hearing from you.

Sincerely,

Andres Cuadros-Meñaca Ph.D.

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Summary of Current Research

Andres Cuadros-Meñaca (ACuadrosMenaca@uams.edu)

Two years ago, I joined the Department of Agricultural Economics and Agribusiness at the University of Arkansas to study the effect of the School Breakfast Program (SBP) in Arkansas under the supervision of Rodolfo Nayga Jr. and Michael Thomsen. Descriptive statistics suggest that many schoolchildren are not taking full advantage of school-provided meals. For instance, participation in school breakfast is much lower than in school lunch. In 2019, only 15 million children participated in the School Breakfast Program (SBP) compared to the nearly 30 million who participated in the National School Lunch Program.

Low participation in the SBP is problematic because there is evidence that breakfast consumption is associated with an improved diet, which enhances cognition among school-aged children. Moreover, Hunger has been shown to impair the development of interpersonal relations and adversely affect classroom behavior. As a response to the low breakfast take-up, schools started implementing breakfast after the bell (BAB), which provides breakfast to students after classes begin. We exploit variation in the adoption of BAB and the exposure by grade to analyze the causal effect of BAB on test scores and disciplinary behavior. Our findings regarding academic performance are published in the *Economics of Education Review* in the article named *The effect of breakfast after the bell on student academic achievement*. Overall we find no impact of BAB on Math and ELA test scores. However, average treatment effects by grade indicate positive effects on math scores for vulnerable children when BAB is adopted in earlier grades. On the other hand, we find improvements in behavior for children in schools that adopted BAB. These results are published in *the American Journal of Agricultural Economics* in the article titled *School breakfast and student behavior*.

Schools in Arkansas have also implemented several provisions to increase participation in school meals by providing free meals for all students (e.g., Community Eligibility Provision CEP). By 2015, of 1,100 schools, 106 provided school meals under the UM's provisions, reaching a total of 325 schools in 2021. We are now analyzing the role of universal meals on behavior and health outcomes such as attention deficit hyperactivity disorder (ADHD) and obesity. I am applying for this fellowship support because several of the sessions are close to my research.

I will benefit from the attendance and interaction with the participants and organizers of the Summer Institute. The SI 2022 Children is organized by Janet Currie, which recently has focused on ADHD and human capital accumulation disparities across children. Moreover, her work with Anna Aizer (also organizer of this session) focuses on school suspensions. On the other hand, I am also working on understanding how the Covid-19 pandemic affected participation in the women, infants, and children (WIC) program. So I am excited about the SI 2022 Health Economics, whose organizers have worked on this topic (e.g., Marianne Bitler's work on Health Impacts of WIC) and obesity (e.g., Christopher Carpenter's work on obesity).

Andres Cuadros-Meñaca

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Academic Positions

Post-Doctoral Associate. Fay W. Boozman College of Public Health, University of Arkansas for Medical Sciences (February 2022-Present).
Post-Doctoral Associate. Department of Agricultural Economics and Agribusiness, University of Arkansas (January 2020-February 2022).
Assistant Professor. Department of Economics, Universidad Icesi (July 2017-January 2020).

Education

PhD, Economics. University of Arkansas 2017.
MA, Economics. University of Arkansas. 2015.
MS, Economics. Universidad Icesi. 2013.
BS, Economics and International Business. Universidad Icesi 2011.

Fields

Applied Econometrics, Applied Microeconomics, Development Economics

Selected Peer-Reviewed Publications

1. The Effect of School Breakfast on Student Behavior: An Evaluation of Breakfast After the Bell (with Michael R. Thomsen and Rodolfo M. Nayga, Jr). *American Journal of Agricultural Economics*.
2. The Effect of Breakfast After the Bell on Student Academic Achievement (with Michael R. Thomsen and Rodolfo M. Nayga, Jr). *Economics of Education Review*. 2022. 86
3. Remittances, Health Insurance, and Pension Contributions: Evidence from Colombia. *World Development*. 2020. 127.
4. Remittances, Child Labor, and Schooling: Evidence from Colombia (with Arya Gaduh). *Economic Development and Cultural Change*. 2020. 68(4), 1257-1293

Other Peer-Reviewed Publications

5. Evaluation of Delivering Breakfast After the Bell and Academic Performance among Third-Grade Children: An Application of the Synthetic Control Method (with Michael R. Thomsen and Rodolfo M. Nayga, Jr). —

Forthcoming: Journal of School Health—

6. South to South Migration: The Impact of the Venezuelan Diaspora on Colombian Natives' Wages and Hours Worked (with Tomas Sayago and Jhon Mora). *Applied Economics Letters*. 2022. 1-8.

7. International Remittances and Children Welfare- A Case Study on Cali Colombia (with Isabella Aguirre and Isabella Borja). *Revista Desarrollo y Sociedad*. 2020. 86, 73-103

8. Family Characteristics and Educational Outcomes in Colombia: An Analysis by Cohorts (with Giovanni Gonzalez and Jhon Mora)" *Revista de Economia Universidad del Rosario*. 2014. 17(1), 157-187

Working Papers

1. Fighting Child Labor with Remittances: Labor Supply Responses to Weather Shocks in China (with Huannan Xu). —*Revised and Resubmitted Journal of Developmet Studies*—

2. Remittances, Schooling, and Social Violence in Colombia (with Jhon J. Mora). —*Under Review*—

Work in Progress

1. Increasing Financial Inclusion via Remittances: Evidence from Colombia (with Arya Gaduh, Andrea Chacon and Andres Ramirez).

2. The Effect of Parental Health Shocks on Non-Cognitive Skills Formation in a Developing Country (with Arya Gaduh and Gema Zamarro).

Teaching

Graduate-level

Applied Microeconometrics, University of Arkansas, Fall 2020.
Research Methods in Migration Studies, Universidad Icesi, Spring 2019.
Advanced Microeconomics II, Universidad Icesi, Spring 2018.
Mathematical and Computational Methods in Economics, Universidad Icesi, Fall 2018.

Undegraduate

Microeconomics Theory III, Universidad Icesi, August 2017-December 2019.
Microeconomics Theory II, Universidad Icesi, August 2017-December 2019.
Basic Economics, University of Arkansas, August 2016-May 2017.
Macroeconomics, Universidad Icesi, January 2013-May 2013.
Macroeconomics Theory II, Universidad Icesi, July 2012-December 2013.

Teaching Assistant

Economic Development, University of Arkansas, August 2016-May 2017.
Econometrics, Universidad Icesi, July 2011-July 2012.

Managerial Economics, Universidad Icesi (MBA) July 2011-August 2013.

Research Assistant

Economics of Education, Universidad Icesi, January 2010-May 2013.
United Nations Program for Development, January 2012-May 2012.
Icecomex, Universidad Icesi, January 2011-July 2011.

Fellowships and Grants

Conferences Fellowships

Sustainability and Development Conference, 2018.
The WIDER Development Conference on Migration and Mobility, 2017.

Fellowships

University of Arkansas Graduate Assistantship, 2016-2017.
Fulbright Scholarship, 2013-2016.
Teaching Assistant Scholarship, Universidad Icesi, 2011-2013.

Professional Activities

Conferences and Seminar Presentations

2022: 19th Midwest International Economic Development Conference (University of Minnesota)
2021: Online Agricultural and Resource Economics Seminar. AAEA & WAEA Joint Annual Meeting
2020: The Economics of Migration Seminar (Online).
2019: Fourth Workshop on Migration, Health, and Well-Being (University of Pittsburgh); 2nd Sustainability and Development Conference (University of Michigan-Ann Arbor.
2018: XXVII Meeting of the Economics of Education Association (Universitat de Barcelona); Sustainability and Development Conference (University of Michigan-Ann Arbor); VI Congreso de Economía Colombiana (Universidad de los Andes); Third International Meeting of Regional and Urban Studies (Universidad Icesi).
2017: 87th Annual Meeting Southern Economic Association (Tampa, FL); The WIDER Development Conference on Migration and Mobility (University of Ghana); 14th Midwest International Economic Development Conference (University of Wisconsin-Madison).
2016: 86th Annual Meeting Southern Economic Association (Washington, DC).
2015: 85th Annual Meeting Southern Economic Association (New Orleans, LA); 52nd Annual Meeting of the MVEA (Kansas City, MO); XXIV Meeting of the Economics of Education Association (Universidad Autónoma de Madrid).
2013: Charlas de Economia (Universidad Icesi).
2012: XXII Simposio Internacional de Estadística (Universidad Industrial de Santander).

Workshops

Mixtape Track Instrumental variables (2022) with Peter Hull.
R toolbox for business school empiricists: Beyond the typical functions as a statistics software (2016) with Guangzhi Shang.
ESTIMATE (2014). With Jeffrey Wooldridge and Timothy Vogelsang. Michigan State.

Referee.

Referee. *World Development*, *Migration Studies*, *Desarrollo y Sociedad*, *Lecturas de Economía*, *Cogent Economics and Finance*, *Educational Economics*
Curriculum Committee, Universidad Icesi, 2017-2019.

Supervised Students

Undegraduate: Isabella Aguirre (Chair), Isabella Borja (Chair), Andrea Chacon (Chair), Andres Ramirez (Chair), Victor Arboleda (Chair), Luis Jordan (Chair).

Graduate: Magaly Herrera (Reader), Sharon Cardenas (Reader).

Miscellaneous

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ARTICLE

School breakfast and student behavior

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Abstract

The School Breakfast Program (SBP) is one of the largest nutrition assistance programs serving school-aged children in the US. It provides reimbursement to states for the operation of breakfast programs in schools. Student participation in the SBP is, however, much lower than the National School Lunch Program (NSLP). Because missing breakfast could result in hunger that could then influence children's interpersonal relations and classroom behavior (i.e., disciplinary infractions), some schools have implemented breakfast after the bell (BAB), which encompasses alternative breakfast delivery methods that make breakfast available to children after the school day commences. We use a difference-in-differences design with variation in BAB exposure across grades to study the effect on children's behavior. We find that infractions drop after schools adopted BAB. Moreover, the impact of BAB on behavior is more pronounced among minority children and those eligible for free and reduced-price meals.

KEYWORDS

breakfast after the bell, breakfast in the classroom, School Breakfast Program, student behavior

JEL CLASSIFICATION

H52, I28

1 | INTRODUCTION

Hunger has been shown to impair the development of interpersonal relations and adversely affect classroom behavior (Howard 2011). Behavior is one pathway through which school nutrition might lead to better outcomes in childhood and over the life course. For example, repeated behavioral

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issues result in a disrupted teaching environment for non-offending students and lead to suspensions (and less instructional time) for the offending students. Moreover, there is growing evidence that disciplinary incidents in school are harbingers of future encounters with the juvenile and adult criminal justice systems (Schaeffer et al. 2003; Wolf & Kupchik 2017; Rosenbaum 2020).

The School Breakfast Program (SBP) aims to reduce hunger for school-aged children in the United States. One factor limiting participation in this program is that children are normally required to arrive at school early, before the school day begins, in order receive breakfast. To address this, many schools have started to provide breakfast after classes start (i.e., breakfast after the bell, hereafter BAB). Given the evidence linking hunger and diet quality to behavioral issues (Benton et al. 2007; Micha et al. 2011), it is possible that increasing participation in SBP through BAB may reduce behavioral infractions among students. The aim of this study is to measure the effect of BAB on both the likelihood of committing an infraction and the number of infractions using data from a statewide public-school system.

We follow 54,087 students who were observed annually from kindergarten (K) to 7th grade using a rich administrative dataset from Arkansas. These data contain information on the number of infractions by each student, including the types of infractions. Arkansas schools began adopting BAB in the 2012–2013 academic year. Because SBP-participating schools have discretion in implementing BAB, some schools did not adopt BAB, whereas others started BAB later during the study period. We compare infractions among children in BAB schools and non-BAB schools through a two-step estimation strategy recently developed by Callaway and Sant'Anna (2020) that exploits this staggered adoption across different grades in school. This methodology provides what Callaway and Sant'Anna (2020) call *group-time average treatment effects*, which we use to compute aggregate causal parameters of the impact of BAB.

We do not find a significantly different likelihood of committing any infractions (the extensive margin). However, we find that attending a BAB school reduces the number of all types of infractions among the subset of students committing one or more infractions during the period of observation, what we term the intensive margin. We estimate that students in BAB schools committed 0.249 fewer infractions per grade. Although this estimate may seem small, it is large relative to the sample mean of 0.699 infractions per child per year. We also focus on infractions for misconduct, aggressive behavior, and miscellaneous infractions classified as "other." When focusing more narrowly on specific types of infractions, we find that attending a BAB school meaningfully reduces the incidence of infractions related to misconduct at both the extensive and intensive margins. We find no evidence of an impact on infractions related to aggressive behavior, nor do we find an impact on other infractions.

There is evidence of treatment-effect heterogeneity by length of exposure (the time continuously spent in a BAB school) and socioeconomic status. Specifically, we find a significant reduction at the extensive margin after four periods of exposure in the commission of any infractions. Lower income children, those qualifying for free and reduced-price meals, and minority children benefitted more from attending a BAB school, which is an important finding because our data show these children are being charged with more infractions overall. Finally, previous studies reported gender differences in children's reactions to acute stress by food insecurity, with girls being more prone to negative behaviors than boys (Rudolph & Hammen 1999; Kudielka et al. 2004; Jyoti et al. 2005). However, we find that both girls and boys benefit equally from attending a BAB school.

This article contributes to the scant literature analyzing the effect of school meal programs and student misbehavior. We build on previous work by Gordon and Ruffini (2018) and Altindag et al. (2020) who present evidence that universal free meals lead to behavioral improvements. Gordon and Ruffini (2018) use variation in the adoption of the Community Eligibility Provision (CEP) across the United States to analyze the effect of free meals on suspension rates. CEP allows schools located in low-income areas to provide free breakfast and lunch to all students. Altindag et al. (2020) study the impact of a free school meal program in South Korea.

Aside from our focus on a breakfast delivery model as opposed to universal free meals, our article differs from these two studies in several other ways: First, we use data at the individual level, which allows us to disentangle several heterogeneous effects and identify students who benefit the most from BAB. Second, we extend the literature on the effects of school meals on students' behavior. This paper is the first to examine treatment heterogeneity by the length of exposure to BAB. Third, unlike Gordon and Ruffini (2018), we focus on infractions as opposed to suspensions. Infractions are the precursor to suspensions and were not available in Gordon and Ruffini's (2018) data. Additionally, although Altindag et al. (2020) use actual offenses, they were unable to identify which South Korean schools participated in the free meal program. Instead, the authors used the share of free meal beneficiaries among the school population to assign the treatment. Moreover, the meal program in South Korea offers a context that is different from that being studied here. Hence, as far as we know, this article is the first to analyze the effect of BAB on disciplinary infractions among schoolchildren. As such, it extends earlier work on the economics of BAB, which has focused primarily on math and reading scores with mixed findings (Imberman & Kugler 2014; Corcoran et al. 2016; Cuadros-Meñaca et al. 2022).

Finally, we provide evidence that our baseline findings are robust to sample composition, model specification, and potential data problems. One specific data problem is that infractions may be underreported because of the possibility of some offenses going undiscovered or the reluctance of school staff to report infractions in some circumstances. This implies that when using infractions as an outcome variable, non-classical measurement error can lead to biased estimates and low power (Millimet & Parmeter 2021). Previous studies ignoring this issue may underestimate the impact of school meals on behavior. Using a stochastic frontier analysis, we find results similar to our baseline estimates.

The remainder of this paper is structured as follows. Section 2 discusses the SBP and the adoption of BAB among schools in Arkansas. Section 3 describes the dataset and the construction of the analytical sample. Section 4 presents the baseline results. Heterogeneous effects are reported in Section 5. Section 6 reports robustness checks. Section 7 concludes.

2 | BACKGROUND

2.1 | Participation in the School Breakfast Program

The SBP is a federally assisted meal program that provides reimbursement to states for the operation of breakfast programs in schools. By 2016, it was estimated that around 15.57 million children participated in the program (USDA 2017). Participating schools are required to serve meals meeting federal nutrition requirements and offer free or reduced-price breakfasts to all eligible children. Eligibility for free or reduced meals is based on family income relative to the federal poverty level.

The Arkansas Department of Education Child Nutrition Unit oversees the SBP in the state. Data on school breakfast participation indicates that between 2015 and 2019, participation rates increased by around 8%. Also, during these years, the number of meals served increased by a similar amount. However, despite this increase, SBP participation is still low relative to the National School Lunch Program (NSLP). In 2019, 65% of Arkansas schoolchildren participated in the NSLP, whereas only 41% participated in the SBP.[1]

Low SBP participation is problematic because breakfast has a myriad of benefits related to nutrition and educational outcomes, especially for those at risk for food insecurity (Bartfeld & Ahn 2011; Fletcher & Frisvold 2017). Ribar and Haldeman (2013) show that universal free breakfast increases participation, and some districts in Arkansas have adopted universal free meals through Provision

[1]Data on breakfast and lunch participation and meals served for Arkansas are available at https://www.fns.usda.gov/pd/child-nutrition-tables.

2 of the National School Lunch Act or under the aforementioned CEP. Provision 2 simplifies meal counting and claiming procedures by allowing schools to serve all meals at no charge for 4 years.

BAB delivery is another strategy that increases participation by ensuring that breakfast can be part of the student's morning schedule. Although Provision 2 and CEP aim to increase participation in the SBP by providing free meals for all, BAB modifies the delivery of the SBP by providing children an opportunity to get breakfast after the school day begins. The Arkansas Hunger Relief Alliance (2015) reports the following statement from a public school principal:

> There's nothing about [BAB] that doesn't work for our kids. The last year that breakfast was served in the cafeteria, the line wrapped around the halls, created delays in the start of class time, and students who were late missed breakfast. This resulted in the counselor's office being swamped with students who were hungry and wanted something to eat. So, she would give those students a breakfast snack. Now that breakfast is served in the classrooms, she no longer becomes the second-string cafeteria.
>
> —Principal, Taylor Elementary School, Jacksonville, Arkansas

The sentiment expressed by this Principal is reinforced by earlier evidence showing BAB increases breakfast participation (Schanzenbach & Zaki 2014; Imberman & Kugler 2014; Corcoran et al. 2016). Overall, the Child Nutrition Tables from the USDA report around a 25% increase in the number of breakfasts served between 2010 and 2019.[2] Some of this increase is likely due to the adoption of BAB delivery models across the United States. Arkansas has one of the highest rates of SBP-participating schools. Even so, Cuadros-Meñaca, Thomsen, and Nayga (2022) estimate that SBP participation is 27% higher in Arkansas BAB schools compared to non-BAB schools.

2.2 | Adoption of breakfast after the bell

In academic year 2012–2013, 135 Arkansas schools went to BAB delivery. This breakfast delivery system has been progressively adopted by other schools and was being used by 443 schools in 2018–2019, the most recent prepandemic schoolyear. There are several BAB delivery models. These include breakfast in the classroom, grab-and-go breakfasts, and second-chance breakfasts (a second breakfast period). Some schools use a combination of these models. However, breakfast in the classroom and grab-and-go are the most common BAB delivery models in our data, accounting for more than half of the BAB-adopting schools in Arkansas (see Figure 1).

The Food Research Action Center, a national advocacy organization on childhood nutrition issues, has developed recommendations regarding the implementation of BAB, suggesting that breakfast in the classroom be implemented for younger children. FRAC's recommendations indicate that grab-and-go and second-chance breakfasts may be more suitable for older children because they provide more flexibility in the morning and do not disrupt the flow of schedule blocks, and older students sometimes report not being hungry early in the morning (FRAC 2017).

The adoption of BAB delivery in Arkansas has been in line with these recommendations (Table A1 in the online supplementary appendix). On average, children in schools using breakfast in the classroom are younger (in lower grades) than those in schools using grab-and-go and second-chance breakfasts. We also observe that the share of minority students and those eligible for free and reduced meals is higher among schools that adopted breakfast in the classroom.

Descriptive evidence from school staff, such as that conveyed in the following quote, suggests that BAB adoption may have positive effects on children's behavior.

[2]Child Nutrition Tables from the USDA Food and Nutrition Service are available at https://www.fns.usda.gov/pd/child-nutrition-tables.

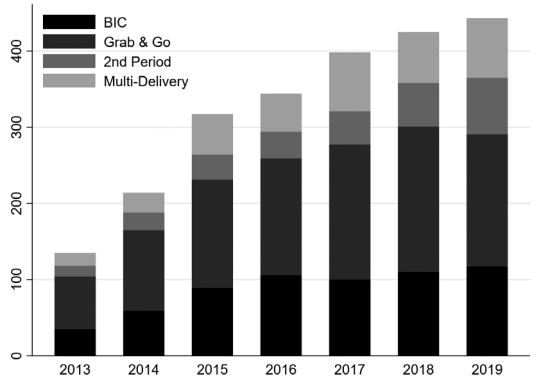


FIGURE 1 BAB adoption and delivery method by year. Figure plots the number of schools adopting BAB and the distribution by delivery method

> By the time noon comes around, if the kids have had nothing, they're hungry. They're cranky. Their heads hurt. They're fidgety. They can't concentrate. So, if they have breakfast in their stomachs, then overall, they have a better day.
>
> – Nurse, Westside School, Jonesboro, Arkansas as cited in Arkansas Hunger Relief Alliance (2015)

We now turn to the evidence on the effect of BAB on disciplinary infractions using statewide administrative data from Arkansas.

3 | DATA

We obtained data through a data-sharing agreement with the Arkansas Department of Education (ADE). These data reflect 1059 to 1097 Arkansas schools, depending on year, between the 2008–2009 through 2018–2019 academic years. They provide student-level information on gender, race or ethnicity,[3] grade level, and school meal status. Moreover, these data indicate whether the child's school adopted BAB, in what year, and if the school provided universal free meals under Provision 2 or the CEP. Because some schools adopted universal free meals, and these policies may impact students' behavior (Gordon & Ruffini 2018), we exclude children in these schools in our baseline estimates. However, as shown below in Section 6, our results and the conclusions drawn from the study are robust to the inclusion of children in schools providing universal free meals. The data also report disciplinary information for the students, including the type and number of infractions. For additional details and descriptions for the various types of infractions, see ADE (2019). Although this is a rich administrative dataset, one limitation is that we do not observe the actual breakfast take-up per student. In fact, school meal counts are only available at the district level. Therefore, our estimates should be interpreted as a reduced form analysis based on intention to treat. Still, intention to treat is useful for policy, especially given that schools have discretion to adopt BAB.

3.1 | Analytical sample

Individual children are the unit of analysis. In our panel, we follow 54,087 children from K to 7th grade for a total of 432,696 observations. Our rationale for the focus on K to 7th grade is supported

[3]Race and ethnicity are mutually exclusive in the ADE student data.

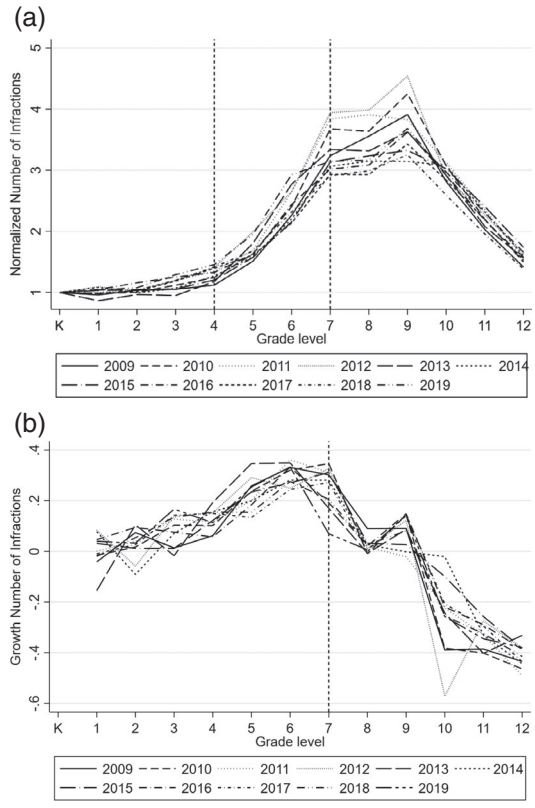


FIGURE 2 Infractions by grade. Infractions are normalized by the number of infractions in kindergarten

by Figure 2, which presents infraction data by grade and year. Panel A presents the trend from K through 12th grade. The trend line for each year is normalized by the number of infractions in kindergarten. Panel B plots corresponding growth rates from this normalized measure. Although Panel A shows that infractions trend upwards through the 9th grade, Panel B shows that the increase in infractions accelerates until the 7th grade. Additional information on the number and type of infractions per year is presented in Figure A1.

Table 1 provides information about the research design and layout of the analysis sample. Columns 1–11 report the cohorts in our analysis. Columns 13 and 14 show that our research design ensures that children from grades K through 2 were not exposed to BAB. This is to provide a pretreatment period to test parallel trends. Column 15 reports the new number of children exposed to BAB by grade. The treatment group comprises children who attended a BAB school for the first time in 3rd grade or later and afterward attended a BAB school in each following grade through the 7th grade. Children who enrolled in a BAB school but later attended a non-BAB school were excluded from the analysis.[4] The comparison group includes children who never attended a BAB school. Our analytical sample is composed of 21,258 students exposed to BAB and 32,829 in the comparison group. By grade and academic year, the upper bound on the range of infractions per child tended to

[4]Detailed information about the students left out from the analysis is presented in Table A2 in the online supplementary Appendix. We found that the percentage of children eligible for a free and reduced-price meal and minority students is larger in the sample of children excluded from the analysis. Those students also report a higher number of infractions. Moreover, excluding children who change BAB status over time ensures that our study design meets Assumption 1 in Callaway and Sant'Anna (2020), which is *irreversibility of treatment*. Once a unit becomes treated, that unit will remain treated in the following periods.

TABLE 1 Data structure

Grade/year	2009 (1)	2010 (2)	2011 (3)	2012 (4)	2013 (5)	2014 (6)	2015 (7)	2016 (8)	2017 (9)	2018 (10)	2019 (11)	Total children (12)	Exposed to BAB (13)	Not exposed to BAB (14)	Newly exposed (15)
K	16,718	13,963	12,048	11,358								54,087		54,087	
1st grade		16,718	13,963	12,048	11,358							54,087		54,087	
2nd grade			16,718	13,963	12,048	11,358						54,087		54,087	
3rd grade				16,718	13,963	12,048	11,358					54,087	1258	52,829	1258
4th grade					16,718	13,963	12,048	11,358				54,087	4462	49,625	3204
5th grade						16,718	13,963	12,048	11,358			54,087	8039	46,048	3577
6th grade							16,718	13,963	12,048	11,358		54,087	12,777	41,310	4738
7th grade								16,718	13,963	12,048	11,358	54,087	21,258	32,829	8481

Note: Columns 1–11 report the number of students by grade and year. Columns 13, 14, and 15 report the number of children exposed to BAB, the number of children not exposed to BAB, and the number of newly children exposed to BAB by grade, respectively.

be in the range of 20 to 35 infractions per child. In only six cases did the maximum number of infractions per child exceed 35; again, these instances were among children in older grades.

3.2 | Measures of disciplinary infractions

Four groupings of disciplinary infractions are considered as outcomes in our models: (1) all infractions, (2) aggressive behavior infractions, (3) misconduct infractions, and (4) other infractions. All infractions include infractions for any reason and averaged 0.268 (SD = 1.253) in the analytic sample. There were 45,608 observations with non-zero infractions among a total of 432,696 child-by-grade observations. Aggressive behavior infractions include offenses such as fighting, bullying, student assault, or staff assault. The mean number of aggressive behavior infractions was 0.033 (SD = 0.239), and there were only 10,709 observations with non-zero infractions for aggressive behavior among the 432,696 observations. Misconduct infractions include offenses disruptive to the learning environment, such as disorderly conduct, insubordination, truancy, and vandalism. There was an average of 0.138 (SD = 0.846) misconduct infractions and 26,483 non-zero observations among the 432,696 observations. Finally, other infractions include contraband items and miscellaneous offenses including those that fall under an "other" category within the ADE data. The average number of other infractions was 0.091 (SD = 0.700), with 19,948 non-zero observations among the 432,696 observations.

To analyze the impact of BAB on those children who commit infractions (the intensive margin), the sample is restricted to include children who committed at least one infraction from K to 7th grade. For all infractions regardless of type, the sample of infraction-committing students included 20,725 (165,800 observations) with an average of 0.699 (SD = 1.948) infractions per year. For misconduct infractions, there were 13,336 children with an average of 0.560 (SD = 1.633) infractions per year. For aggressive behavior infractions, there were 7144 children with an average of 0.248 (SD = 0.617) infractions per year. Finally, 12,193 children who report having at least one infraction from the "other" category with an average of 0.403 (SD = 1.234) infractions per year.

4 | BASELINE ANALYSIS AND FINDINGS

4.1 | Empirical strategy

We estimate the effect of attending a BAB school on disciplinary infractions using difference-in-differences (DiD) with variation in treatment timing. Because of the staggered exposure to BAB by grade, we follow the two-step procedure in Callaway and Sant'Anna (2020). This procedure is robust to treatment effect heterogeneity that results from differences in time of first exposure and length of exposure. We consider the case with eight periods, $T = 8$, denoted by the grade of the student $g = K, \ldots, 7$. Given the study design explained above, the earliest possible exposure to BAB is during the 3rd grade, and we define gt as the period when a student first attends a BAB school. The methodology in Callaway and Sant'Anna (2020) centers on calculating what the authors call a *group-time average treatment effect*, which in our case consists of a unique average treatment effect on the treated (ATT) for a cohort of students who are exposed to BAB during the same grade. When pretreatment covariates play no role in the identification, Callaway and Sant'Anna (2020) prove that consistent estimates of the group-time ATT can be obtained by computing:

$$ATT(gr,g) = E\left[Y_g - Y_{gt-1} | G_{gr} = 1\right] - E\left[Y_g - Y_{gt-1} | C = 1\right], \quad (1)$$

where Y_g is the outcome variable at grade g, and gr denotes the group first attending a BAB school at time gt. Note that this equation resembles the canonical average treatment effect on the treated in a DiD setup with two time periods. The second term on the right of Equation 1 is the counterfactual with $C = 1$ for children in the comparison group.[5] However, this extension uses Y_{gt-1} infractions before BAB started for each group. The identifying assumption is that average outcomes for the group first treated in period g and for the comparison group (the never-treated group) would have followed parallel paths in the absence of treatment. Moreover, we assume no anticipation (Callaway and Sant'Anna 2020). This assumption is reasonable because schools decide whether to implement BAB not the individual children.

Last, we aggregate these individual ATT parameters by group following Callaway and Sant'Anna (2020, p. 209) to show the effects of BAB overall and by the length of exposure. The inference is based on their multiplier bootstrap procedure with clustering at the school level.[6]

4.2 | Group-time average treatment effects

Figures 3 and 4 present group-time ATTs from Equation 1 along with 95% confidence bands for the extensive margin (probability of positive infractions) and the intensive margin (number of infractions), respectively. The ATTs were estimated under the assumption of unconditional parallel trends. One important feature of the group-time average treatment effect parameters is that they do not directly restrict heterogeneity with respect to observed covariates. Nevertheless, results including covariates are presented as a robustness check in Section 6 and in the online supplementary Appendix. Figures 3 and 4 are for all infractions, but similar plots are presented in the online supplementary Appendix for specific types of infractions in Figures A2–A4. Two main results emerge from the figures: First, the plots include pretreatment estimates that can be used as evidence of parallel trends. None of the point estimates in the pretreatment periods (outside of the gray areas of Figures 3 and 4) are significantly different from zero, which is consistent with parallel trends. Second, many effects in the post-treatment periods (point estimates inside the gray area) in Figure 4 are significant or very close to being significant for 6th and 7th graders who first attended BAB schools in 3rd through 6th grades, suggesting that BAB reduces the number of infractions.

4.3 | BAB and disciplinary infractions

Table 2 presents baseline results by type of infraction. The first row reports the average effect of attending a BAB school across all grade groups.[7] The striking feature in Table 2 is the large and significant reductions in the misconduct infractions at both the intensive and extensive margins. The point estimate for the number of infractions is −0.383, which in absolute value accounts for almost 68% of the mean number of misconduct infractions per child per year (0.560). Attending a BAB school also operates on the extensive margin for misconduct infractions. Table 2 shows a significant decrease in the likelihood of committing this type of infraction. There is no significant effect on aggressive behavior or "other" infractions, so the large reduction in misconduct infractions is driving

[5]Because we have a sizeable group of children who were never exposed to BAB, we favor Assumption 4 in Callaway and Sant'Anna (2020), and use the never exposed children as a comparison group instead of not-yet-exposed. Using this latter group involves potential drawbacks in that it restricts observed pretreatment trends across groups. Nevertheless, we report results in Table A14 in the online supplementary Appendix that include the not yet exposed children in the comparison group.

[6]While we were working on this study, Wooldridge (2021) proposed an alternative method to compare treated to not-yet-treated units using the standard two-way fixed effects model. We do not pursue this alternative method here as it is beyond the scope of this paper and, at the time of writing this article, had not been through peer review.

[7]The aggregation schemes for the $ATT(gr,g)$'s in Callaway and Sant'Anna (2020) are of the form $\theta = \sum_{gr \in G} \sum_{g+1}^{T} w(gr,g) \cdot ATT(gr,g)$, where $w(gr,g)$ are the non-negative weights for aggregated parameters.

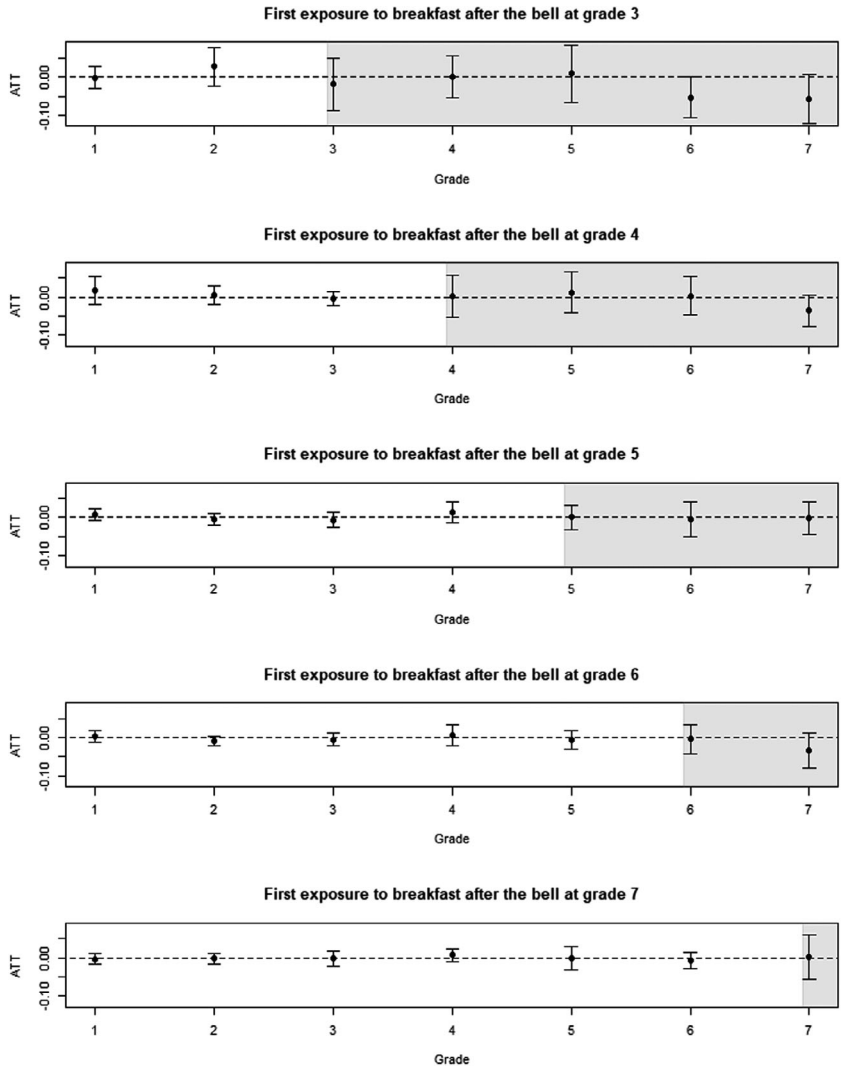


FIGURE 3 Group-time average treatment effects for the marginal probability of positive infractions. Point estimates and 95% confidence bands for pre- and post-treatment periods are outside and inside the gray shaded area, respectively. Confidence bands are based on standard errors clustered at the school level

the result that all infractions decline by −0.249 after schools went to BAB. Again, this may seem small, but the sample mean for all infractions is 0.699.

Figure 5 presents event-study-type estimates to explore treatment effect heterogeneity concerning the length of time spent in a BAB school. Event time is expressed as the time elapsed since first enrollment in a BAB school. Figure 5 plots the average effect of exposure to BAB, e grades after first exposure across all groups who were exposed for exactly e grades. For example, when $e = 0$ (the contemporaneous effect of BAB), all groups are reflected in the effect. However, when $e = 1$, the ATTs only reflect children first exposed to BAB during 3rd–6th grades. This is because those first exposed in 7th grade only have a contemporaneous ATT ($e = 0$).

In Figure 5, the point estimates and 95% confidence bands for pretreatment and post-treatment periods are shown in red and blue, respectively. Figure 5 provides additional evidence in favor of the parallel-trends assumption in that none of the point estimates during the pretreatment periods are

statistically different from zero, and the 95% confidence bands are narrow. Although this type of event study can suffer from differences in composition groups, it does complement the results presented above. The primary takeaway is that duration of exposure matters, as shown by the downward trend in the probability of any infractions (left panel) and in the number of infractions (right panel). For all infractions, Panel A shows significant effects during the fourth period of exposure at the extensive margin and during the fourth and fifth periods of exposure at the intensive margin. For infractions related to misconduct, Panel B shows statistically significant effects during the first two periods of exposure and the fourth period, but these are only significant at the intensive margin (right panel). In contrast to the findings presented above, Panel D of Figure 5 also shows a significant negative effect on the marginal probability of having positive infractions and a reduction in the number of other types of infractions for those exposed to BAB for four and five periods. Again, there is no evidence of an effect for infractions related to aggressive behavior (Panel C).

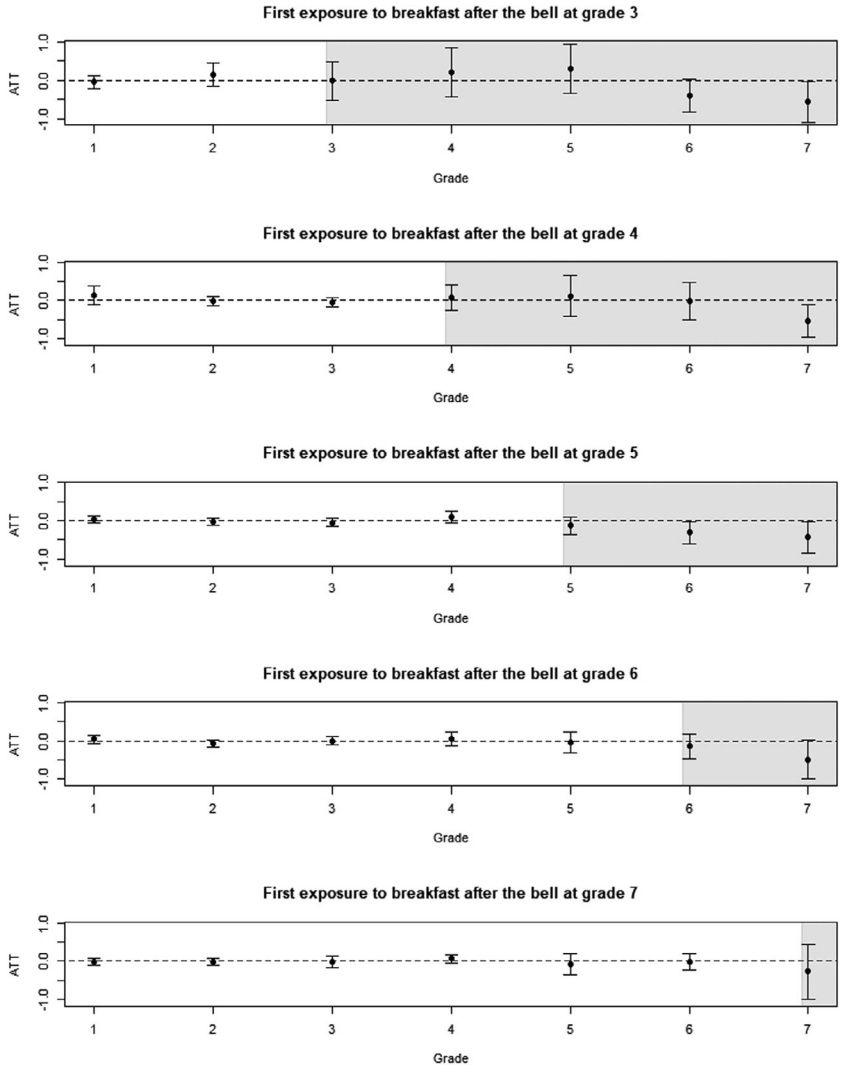


FIGURE 4 Group-time average treatment effects for total number of infractions. Point estimates and 95% confidence bands for pre- and post-treatment periods are outside and inside the gray shaded area, respectively. Confidence bands are based on standard errors clustered at the school level

TABLE 2 The effect of BAB on disciplinary infractions

	All		Misconduct		Aggressive behavior		Other	
	Extensive margin (1)	Intensive margin (2)	Extensive margin (3)	Intensive margin (4)	Extensive margin (5)	Intensive margin (6)	Extensive margin (7)	Intensive margin (8)
BAB	−0.005	−0.249**	−0.018***	−0.383***	−0.001	−0.001	0.003	0.005
	(0.009)	(0.109)	(0.006)	(0.083)	(0.003)	(0.033)	(0.009)	(0.140)
Observations	432,696	165,800	432,696	106,688	432,696	57,152	432,696	97,544
Mean of:								
Positive infractions (%)	10.54	27.51	6.12	24.82	2.47	18.74	4.61	20.45
Infractions (No.)	0.268	0.699	0.138	0.560	0.033	0.248	0.091	0.403

Note: Results at the extensive margin reports the marginal change in the probability of having positive infractions. Results at the intensive margin report the effect of BAB on the number of infractions committed. The first row reports the weighted average of all available grade-time average treatments. Standard errors in parentheses are clustered at the school level. Share of observations with positive infractions and average infractions are reported at the bottom of the table. Estimates in even-numbered columns are computed from restricted samples containing children with at least one infraction of the specified type from grades K to 7.
**p <0.05, ***p <0.01.

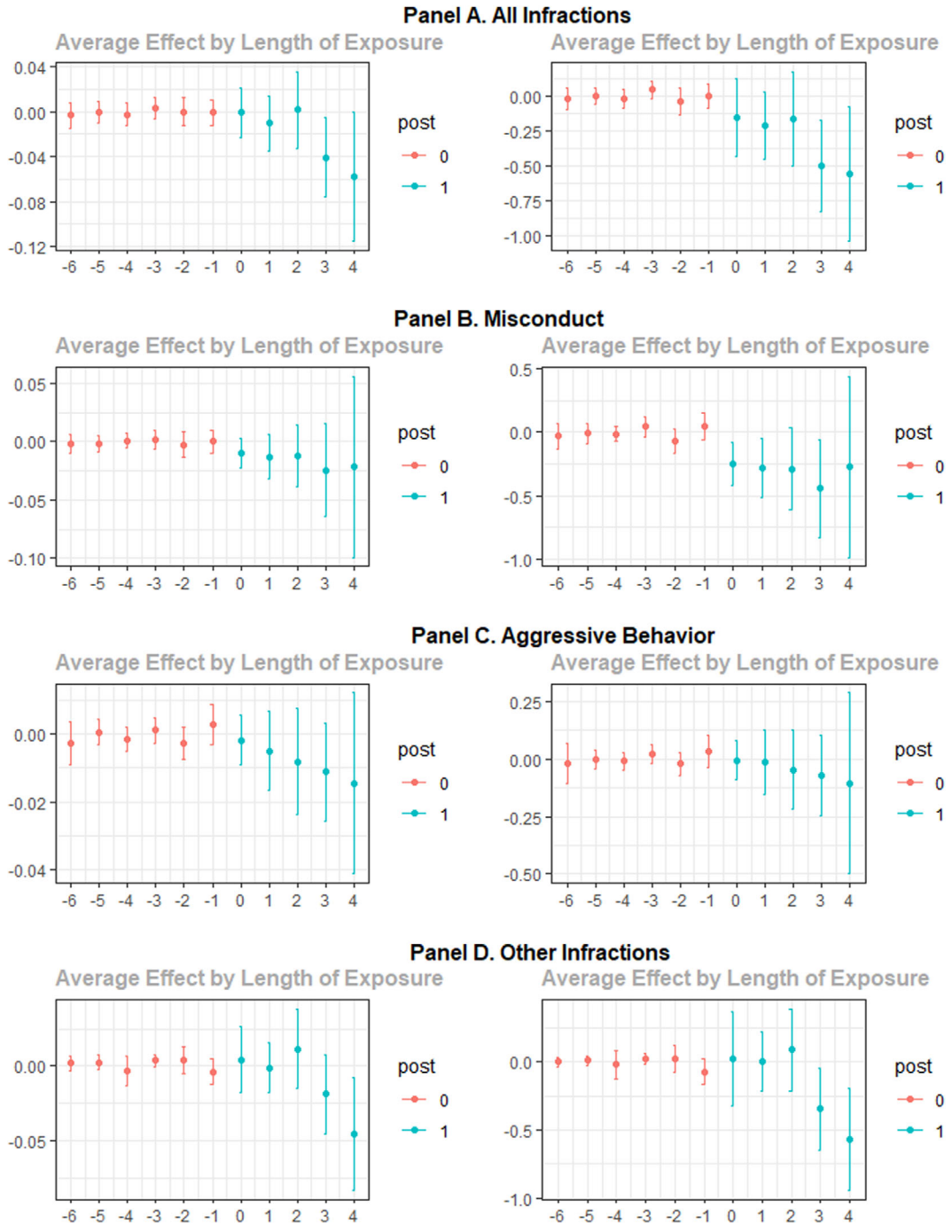


FIGURE 5 Dynamic average treatment effects. The left column reports the effect on the likelihood of committing positive infractions, and the right column reports the effect of BAB on the number of disciplinary infractions. Red lines give point estimates and 95% confidence bands for pretreatment periods. Blue lines provide point estimates and 95% confidence bands for the treatment effect of attending a school with BAB. Confidence bands are based on standard errors clustered at the school level

5 | HETEROGENEOUS EFFECTS

5.1 | Socioeconomic and demographic characteristics

School meal programs have been shown to disproportionately benefit children in families with poor home food environments (Smith 2017). Although BAB aims to increase the availability of school breakfast for all children, there may be disproportionate benefits in terms of behavioral improvements among children at greater risk for hunger or poor diet quality. To address this question, the analysis was repeated for subsamples of lower income children (those who qualify for free or reduced-price meals) and more affluent children. Because eligibility may change across periods, we compared those children who were never classified as eligible for free and reduced-price meals (always above 185% of poverty) to those who were classified as eligible at least once during grades K–7 (were below 185% of poverty at least once during their K–7 tenure in the public schools). This decision follows Gordanier et al. (2020) by including children who may switch income status across grades and thus be at risk for food insecurity even though they were not always in low-income households. Heterogeneity was also assessed by repeating the analysis for subsamples by minority status (minority vs. non-Hispanic white students) and by gender.

Table 3 presents BAB effects along with the average prevalence of any infractions and the number of infractions across subsamples by meal status, minority status, and gender. As shown in the table, students eligible for free or reduced-price meals, minority students, and boys were, on average, more likely to be charged with any infractions and had higher numbers of infractions. Panels A and B of Table 3 show that the effect of BAB at the intensive margin is only significant for lower income and minority children. Although it is not possible to directly test the mechanism whereby BAB disproportionately benefits lower income and minority students, these findings are consistent with earlier studies indicating that children in economically or socially disadvantaged families are more likely to be food insecure, which may contribute to psychosocial dysfunction (Kleinman et al. 1998; Alaimo et al. 2001).

Results by gender are reported in Panel C of Table 3. Point estimates for boys and girls are similar in magnitude and statistically significant at the 10% and 1% level, respectively. Point estimates suggest that both groups benefit from BAB. Moreover, we also compare elasticities to account for the fact that boys commit more infractions and find no statistical differences in BAB effects by gender using an independent sample t-test. In the interest of space, group-time average treatment effects for the subsamples by meal status, minority, and gender are not reported here but are summarized in Figures A5–A10 in the online supplementary Appendix.

5.2 | BAB delivery method

Heterogeneity was also explored by type of BAB delivery model: breakfast in the classroom, grab-and-go, and second-chance breakfasts. Of the 21,258 children who were in the BAB treatment group, 931 were always in schools offering breakfast in the classroom, 8739 were in schools using a grab-and-go model, and 3319 were in schools that provided second-chance breakfast periods. The rest of the students were in schools using a combination of these models or encountered different delivery models over time as they advanced through the school system.

Estimates by delivery model in Table 4 are consistent with those reported earlier, in that we do not find evidence of a BAB effect at the extensive margin across all infractions. Table 4 suggests children in BAB schools that provide breakfast in the classroom are driving the overall results at the intensive margin. The strongest evidence of a BAB effect is among these students. A statistically significant effect is observed among BAB children who attended schools using the second-chance model, but this is of marginal statistical significance. Given the aforementioned evidence that breakfast in the classroom is a more common model among elementary schools, these findings suggest that implementing BAB

TABLE 3 Heterogenous effects by meal status, minority status, and gender

	Extensive margin (1)	Intensive margin (2)	Extensive margin (3)	Intensive margin (4)
	Panel A. Free and reduced-price meal status			
	Eligible		**Non-Eligible**	
BAB	−0.007	−0.235***	−0.007	−0.259
	(0.008)	(0.091)	(0.015)	(0.179)
Observations	295,296	135,432	137,400	30,368
Mean of:				
Positive infractions (%)	13.16	28.70	4.91	42.64
No. infractions	0.348	0.760	0.094	0.426
	Panel B. Minority status			
	Minority		**Non-minority**	
BAB	−0.017	−0.296**	0.002	−0.152
	(0.013)	(0.138)	(0.011)	(0.118)
Observations	114,296	55,936	318,400	109,864
Mean of:				
Positive infractions (%)	15.23	31.13	8.86	25.67
No. infractions	0.456	0.931	0.200	0.580
	Panel C. Gender			
	Boys		**Girls**	
BAB	−0.001	−0.229*	−0.010	−0.284***
	(0.012)	(0.128)	(0.008)	(0.083)
Observations	216,632	107,368	216,064	58,432
Mean of:				
Positive infractions (%)	14.99	30.24	6.08	22.50
No. infractions	0.398	0.803	0.137	0.507

Note: Results at the extensive margin reports the marginal change in the probability of having positive infractions. Results at the intensive margin report the effect of BAB on the number of infractions committed. The first row or each panel reports the weighted average of all available grade-time average treatments. Standard errors are in parentheses and are clustered at the school level. Share of observations with positive infractions and average infractions are reported at the bottom of each panel. Estimates in even-numbered columns are computed from restricted samples containing children with at least one infraction from grades K to 7.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

among schools serving younger children may be important in terms of reducing infractions over the tenure in the school system. Note that each subsample includes the entire set of children in the non-BAB schools. Group-time average treatment effects for the subsamples by BAB delivery model are summarized in Figures A11–A13 in the online supplementary Appendix.

6 | ROBUSTNESS CHECKS

We now turn to the sensitivity of our baseline findings reported in Section 4. First, we consider two additional samples. One is an expanded sample that includes children in schools that provided universal free meals. As noted in Section 3, we excluded children in schools providing universal free meals in our baseline estimates because universal free meals would be expected to increase breakfast participation regardless of BAB (Ruffini 2021) and have previously been associated with reductions

TABLE 4 Heterogeneous effects by BAB delivery model

	BIC		Grab-and-go		Second chance	
	Extensive margin (1)	**Intensive margin (2)**	**Extensive margin (3)**	**Intensive margin (4)**	**Extensive margin (5)**	**Intensive margin (6)**
BAB	−0.031	−0.471***	0.002	−0.109	−0.053	−0.836*
	(0.020)	(0.181)	(0.011)	(0.103)	(0.044)	(0.463)
Observations	270,080	104,504	332,544	127,512	289,184	112,128
Mean of:						
Positive infractions (%)	10.93	28.26	10.65	27.76	10.98	28.32
Infractions (No.)	0.291	0.751	0.278	0.725	0.290	0.748

Note: BIC refers to breakfast in the classroom. Results at the extensive margin reports the marginal change in the probability of having positive infractions. Results at the intensive margin report the effect of BAB on the number of infractions committed. The first row reports the weighted average of all available grade-time average treatments. Standard errors are in parentheses and are clustered at the school level. Share of observations with positive infractions and average infractions are reported at the bottom of the table. Estimates in even-numbered columns are computed from restricted samples containing children with at least one infraction from grades K to 7. Each subsample includes all observations from the comparison students (those in non-BAB schools).

*p <0.10, ***p <0.01.

TABLE 5 The effect of BAB on disciplinary infractions for alternative samples and model specifications

	Universal free meals		K–9		Conditional parallel trends		Fixed effects		Skewed measurement error
	Extensive margin (1)	Intensive margin (2)	Extensive margin (3)	Intensive margin (4)	Extensive margin (5)	Intensive margin (6)	Extensive margin (7)	Intensive margin (8)	Intensive margin (9)
BAB	−0.006	−0.240***	−0.005	−0.156*	−0.004	−0.158*	−0.005	−0.201**	−0.200*
	(0.008)	(0.092)	(0.008)	(0.089)	(0.009)	(0.094)	(0.010)	(0.099)	(0.104)
Observations	495,744	200,536	231,240	113,210	432,696	165,800	432,696	165,800	165,800
Mean of:									
Positive infractions (%)	11.45	28.30	12.43	25.38	10.54	27.51	10.54	27.51	27.51
Infractions (No.)	0.301	0.744	0.329	0.673	0.268	0.699	0.268	0.699	0.699

Note: Results at the extensive margin reports the marginal change in the probability of having positive infractions. Results at the intensive margin report the effect of BAB on the number of infractions committed. Columns 1–4 report aggregated treatment effect parameters with clustered standard errors in parenthesis at the school level. Columns 5 and 6 report aggregated treatment effect parameters under the conditional parallel trends assumption using doubly robust estimator in Callaway and Sant'Anna (2020). Columns 7 and 8 report BAB estimates using a model with time, group, and grade effects. Column 9 presents BAB estimates from the stochastic frontier analysis (SFA). Estimates in even-numbered columns are computed from restricted samples containing children with at least one infraction from grades K to 7.
*p <0.10, **p <0.05, ***p <0.01.

in suspension rates among elementary and middle school students (Gordon & Ruffini 2018). However, schools offering universal free meals through the CEP or Provision 2 are likely to be lower income schools, and exclusion of students from these schools makes our baseline sample less representative of Arkansas as a whole. The other additional sample includes infractions in grades 8 and 9 and consists of children who could be followed from grades K–9. As explained above, the choice to include grades K–7 was based on growth in infractions, which shows a marked decline after grade 7 (Panel b of Figure 2). However, total infractions continue to increase through grade 9 (Panel a of Figure 2). In any case, there is a need to verify that our baseline findings are robust to the ranges of grades included.

Next, we consider alternative analyses using our original baseline sample to further assess the sensitivity of our findings. First, we estimate BAB effects under the weaker assumption of conditional parallel trends. Second, we investigate the potential impact of skewed, non-classical measurement error as a result of the possible under-reporting of disciplinary infractions.

Group-time average treatment effects for the subsamples analyzed in this section and under conditional parallel trends are summarized in Figures A14–A16 in the online supplementary Appendix.

6.1 | Alternative samples

After including children in schools providing universal free meals, the new sample exposed to BAB increases to 24,904 children in the treatment group. The number of children in the comparison group increases to 37,064. Columns 1 in Table 5 reports the average effect of being exposed to BAB

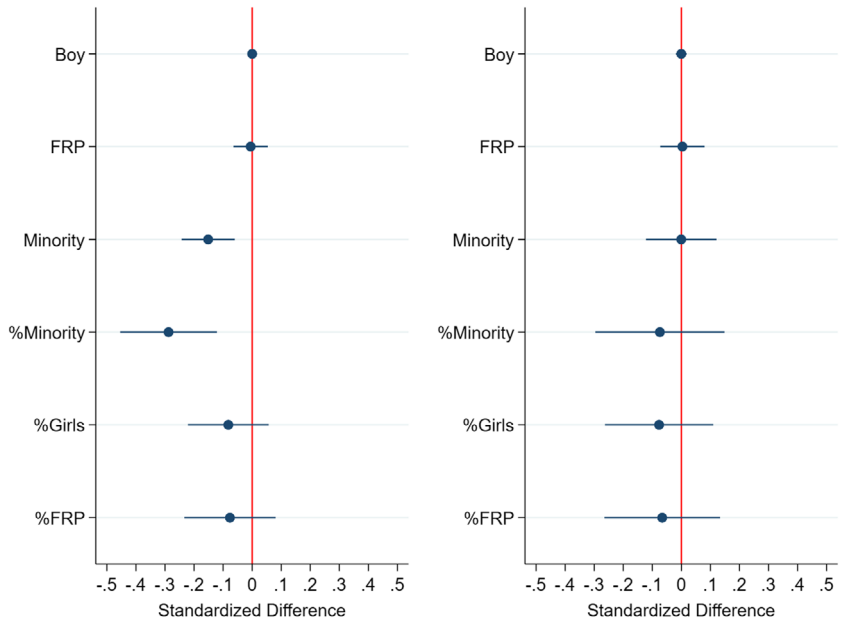


FIGURE 6 Unconditional (Panel a) and conditional (Panel b) differences between children exposed to BAB and the comparison group. To obtain standardized differences, we estimate the regression $X_{it} = \beta_0 + \beta_1 BAB_{it} + \epsilon_{ig}$ where X_{it} is an individual or school attribute of child i including whether the child is a boy, *Boy*, eligible for free and reduced-price meal, *FRP*, and classified as non-white, *Minority*. Also, the percentage of children classified as non-white in the school, *% Minority*, the percentage of girls in the school, *% Girls*, and the percentage of children eligible for federal meals in the school, *% FRP*. BAB_{it} is an indicator variable that takes the value of one when child i is exposed to BAB. Then, we divide the estimate β_1 by the standard deviation of the attribute. Conditional standardized differences include grade, year, and group fixed effects. Standard errors are clustered at the school level

at the extensive margin, and Column 2 the effect of BAB at the intensive margin—children with at least one infraction from grades K through 7—from this updated sample. The estimates at both the extensive and intensive margins are similar to the baseline results in Table 2 in terms of magnitude but with an effect at the intensive margin that is statistically significant at the 1% level.

Columns 3 and 4 in Table 5 report results when increasing the panel time dimension from grades K–7 to grades K–9. As shown by the number of observations for these columns, there is a cost of expanding the sample to include infractions through the 9th grade because the number of children in a panel that we can follow over the K–9 period is smaller. Nevertheless, the findings are again similar to those reported in Table 2. We find that children exposed to BAB commit 0.156 fewer infractions at the intensive margin.

6.2 | Conditional parallel trends

In the baseline empirical strategy, identification does not depend on controlling for covariates. However, it hinges on the assumption that in the absence of treatment, the average outcomes for treated and comparison groups would have followed parallel paths over time. Although we provide evidence on parallel pre-intervention trends above, additional concerns may remain. Thus, we consider Abadie's (2005) idea of *conditional parallel trends*. The threat to identification may arise when covariates are imbalanced between treatment and comparison groups or because covariates explain the selection into treatment itself.

We follow Altindag et al. (2020) and present standardized differences by exposure to BAB in Figure 6. Each individual and school covariate was regressed on the BAB indicator. The estimate was then divided by the standard deviation of the covariate. Panel A shows that children exposed to BAB are less likely to be classified as a minority and less likely to attend a school with a larger percentage of minority students.[8] Panel B presents conditional standardized differences in that the regressions also included grade, year, and group fixed effects. The estimates in panel B no longer show significant differences between BAB and non-BAB students after inclusion of these fixed effects. In both panels, standard errors were clustered at the school level.

We implement the estimator in Callaway and Sant'Anna (2020) with conditional parallel trends to address this potential threat to our identification strategy. As in Abadie (2005), we use pretreatment covariates in a propensity score that absorbs the information on the covariates to pair units in the treatment and comparison group.[9] Although ignoring the presence of covariate-specific trends can bias the estimates, the results in Columns 5 and 6 of Table 5, which were estimated with conditional parallel trends, indicate that the inclusion of the covariates does not qualitatively affect our results. Tables A10–A12 in the online supplementary Appendix present additional estimates under conditional parallel trends by meal status, minority status, gender, and type of BAB delivery. Table A13 does the same for the additional analytic samples (including universal meals and K–9 students).

6.3 | Skewed measurement error

As noted above, there is the possibility that some disciplinary infractions are under-reported. Thus, the true number of infractions is likely to exceed the observed number ($Y^*_{it} > Y_{it}$). Millimet and Parmeter (2021) show that this type of non-classical measurement error can be problematic, leading

[8]Summary statistics for covariates at the individual and school levels comparing children exposed to BAB and in the comparison group are provided in Table A3. An analysis by grade level is also reported in Tables A4–A9. Except for gender, the differences between the BAB and comparison groups are significant at conventional levels.

[9]This adjustment is made using pretreatment covariates following the recommendations of Wooldridge (2005) and Callaway and Sant'Anna (2020).

to biased estimates. They also show that stochastic frontier analysis (SFA) can address this issue when the dependent variable is continuous. Given that Panel b in Figure 6 shows that the standardized differences disappear after conditioning on grade, year, and group fixed effects, we first specify a fixed-effects model as follows:

$$Y_{it}^{*} = \alpha_g + \alpha_{gr} + \lambda_t + \beta BAB_{it} + \mathbf{X}_{it}\Pi + \epsilon_{it}, \tag{2}$$

where Y_{it}^{*} captures the number of infractions. α_g is the grade fixed effect, α_{gr} is the group effect, and λ_t is the year effect. BAB_{it} is a binary variable taking the value of one when the child is exposed to BAB. The stochastic frontier model is given by:

$$Y_{it} = \alpha_g + \alpha_{gr} + \lambda_t + \beta BAB_{it} + \mathbf{X}_{it}\Pi - u_{it} + \varepsilon_{it}, \tag{3}$$

where

$$Y_{it} = Y_{it}^{*} - u_{it},$$

Y_{it} is the observed value of Y_{it}^{*}. We assume that the one side error is distributed half normal and model the variance in the error term as:[10]

$$\sigma_{uit}^{2} = \exp(Z_{it}\gamma).$$

Although we cannot use the stochastic frontier analysis (Equation 3) to model the extensive margin, we do examine the extensive margin within the fixed effects model (Equation 2). This is to facilitate comparison with findings reported earlier from the Callaway and Sant'Anna (2020) method.

Estimates from Equations 2 and 3 are reported in Columns 7 to 9 of Table 5. Standard errors were clustered at the school level. Again, in Column 7, we find no evidence that BAB exposure has an effect at the extensive margin. A comparison of Columns 8 and 9 shows that the stochastic frontier specification does little to alter the estimate at the intensive margin. These estimates are also close to the baseline estimate in Column 2 of Table 2.[11] The conclusion is that skewed measurement error is not leading to a meaningful bias in the estimate of the BAB effect at the intensive margin. Complete estimates from Equation 2 are in Tables A15–A18 in the online supplementary Appendix.

7 | CONCLUSIONS

The School Breakfast Program is a federally assisted meal program that provides millions of children a nutritious morning meal each school day. To address low rates of participation, some schools have implemented BAB to make breakfast available to students after classes begin. Without BAB, children would need to arrive at school early, before classes start, in order to receive school breakfast. BAB increases availability because children are able to eat breakfast in their classrooms, on the way to the classroom, or during morning breaks. Because BAB is associated with increases in participation in breakfast meals, and given the link between reducing hunger and behavioral issues, we analyzed

[10]Similar to the application on criminal activity in Millimet and Parmeter (2021), we excluded the other fixed effects in the variance of the error term. These omissions were required as otherwise the model does not converge.

[11]We also estimate the impact of BAB on the CDF of the number of infractions following Powell (2020). Figure A17 in the online supplementary Appendix shows that BAB does not statistically affect the probability of committing any infractions. However, it shows that attending a school that adopted BAB decreases the probability of committing less than four infractions when considering all violations and three infractions related to misconduct. We find no evidence that BAB impacts students' behavior when analyzing infractions related to aggressive behavior and other types of infractions.

whether BAB impacts the likelihood of committing any infractions and the number of infractions using rich administrative data from Arkansas.

We find robust evidence that BAB meaningfully reduces infractions primarily at the intensive margin, meaning that those children who were charged with infractions committed fewer of them after their schools went to BAB. Because the number of infractions is higher among lower income and minority children, our findings suggest that BAB may be one way to reduce disparities in school discipline over the socioeconomic gradient.

Moreover, our results suggest that BAB may be a cost-effective way to improve behavior, especially from the perspective of local schools and school districts. As a back-of-the-envelope analysis, consider that child nutrition tables show that Arkansas schoolchildren were served 32,353,877 school breakfast meals in academic year 2018–2019, the last year in our analysis (USDA-FNS 2021). In 2018–2019, state enrollment figures indicate that 39.5% of Arkansas schoolchildren were in grades 3 through 7, and we estimate that 38% of these children were in BAB schools. Given earlier estimates that BAB increased Arkansas breakfast participation by 27% (Cuadros-Meñaca et al. 2022), this would translate into roughly 1,311,205 additional breakfasts served to 3rd to 7th graders as a result of BAB. Scaling down the point estimate reported earlier in Column 2 of Table 2 by ratio of students with one or more infractions to total students, we get a per-student reduction of 0.095 infractions. When multiplied by the total enrollment of 188,758 in grades 3 to 7 in 2018/2019, this translates into 17,932 fewer infractions in BAB schools.

To translate this into monetary terms, the average total cost of a breakfast meal is proxied by the reimbursement rate for breakfast in 2019, which was $2.09 (Arkansas Department of Human Services 2021). Imberman and Kugler (2014) report that costs per meal in BAB schools were 75% of non-BAB schools, largely due to economies of scale in breakfast delivery. This is not surprising. There will be excess capacity in the mornings when breakfast is served because school foodservice infrastructure is scaled to the lunch program, which as noted above, has much higher rates of participation. However, the increase in breakfast participation that Imberman and Kugler (2014) referenced is more dramatic than the one experienced in Arkansas because participation was already high relative to other areas of the US. Assuming that BAB schools in Arkansas experienced only half of the per-meal cost savings referenced in Imberman and Kugler (2014), moving to BAB would have cost an additional $2,397,866 in meal costs, which would translate into roughly $134 per infraction avoided. However, this simple calculation does not include other human capital gains resulting from increased breakfast participation nor does it include the savings in staff time that would result from having fewer behavioral incidents at school. At the local level, the additional meal costs would largely be offset by additional revenue going to the child nutrition program, suggesting that BAB is a low-cost way to improve behavior from the perspective of schools and districts.

As noted earlier, one limitation of this study is that the actual breakfast take-up per student is not observed. In fact, school meal counts are available only at the district level. Because of this, our estimates on behavior should be interpreted as a reduced form analysis based on intention to treat. Nevertheless, intent-to-treat effects are of interest to decision makers assessing BAB adoption, given schools' discretion to adopt this alternative delivery method. Related to this limitation is that we are unable to explore how students and parents respond after schools adopt BAB or other mechanisms behind the adoption of BAB. For instance, it would be of interest to know the extent to which BAB reaches children who are currently missing their breakfast under the traditional delivery of the SBP due to avoidance of stigma or late arrival to school. Given the stronger effects among economically disadvantaged students, we suspect that BAB is in fact making breakfast more accessible to those who might otherwise not be having breakfast in the morning. However, future work should focus on these and other mechanisms. Another limitation of the present study is that the methods used here required continued observation of children from kindergarten through 7th grade. Those excluded for reasons of incomplete observation were more likely to be minority children and lower income children, the same kinds of children who we show benefit the most from BAB. The benefits of BAB for these excluded children may be higher than those reported here.

Despite these limitations, these findings contain several insights that may be of use for policymakers. First, advocates of delivering breakfast after the bell may use these results to show that the benefits of BAB extend beyond outcomes like academic test scores. Second, our results provide additional evidence that children at higher risk of food insecurity may benefit the most when accessing the SBP. Third, we provide novel evidence that the type of delivery method may have different results, with breakfast in the classroom being more effective. This latter result may actually be showing the importance of breakfast early in childhood as this delivery method was more common among elementary schools.

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