Taking the Long Way Home: The Effects of Bus Commutes on Student Achievement

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Abstract

I estimate the causal impact of commuting time on students' academic effort and performance. Using novel administrative transportation data from North Carolina and idiosyncratic variation in bus route assignments, I show that longer bus commutes worsen student outcomes. A one standard deviation (21.5-minute) increase in morning commuting time leads to a 2.6 percent increase in the likelihood of being suspended, a 0.01 s.d. decrease in math and reading test scores, and a 0.02 s.d. decrease in ACT score. Time use patterns suggest students and adults respond similarly when faced with long commutes—sacrificing sleep and potentially diminishing their productivity.

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1 Introduction

Commutes are significant components of the workday for most workers in the United States. On average, labor force participants travel about 27 minutes to their jobs, with almost 10 percent traveling over an hour to get to work. (US Census Bureau 2023) A growing literature shows that this daily travel negatively impacts workers' effort and productivity on the job. (Xiao, Wu, and Kim 2021; Ross and Zenou 2008; Van Ommeren and Gutiérrez-i-Puigarnau 2011) Similarly, K-12 students begin their days by commuting to school. Students often live relatively close to their schools, leading to short commutes if they can travel by car or on foot; however, many public school students commute on school-provided buses. During the 2022-2023 school year, 44 percent of public K-12 students in the United States commuted by bus. (School Bus Fleet 2023) Schools tend to load their buses to capacity to minimize their transportation costs, leading to long, indirect routes to school for many students.

There is little causal evidence on how commutes impact workers. Measuring the causal effect of commutes on performance is challenging because people consider their potential commute when selecting their housing and job. If workers who are more dedicated to their jobs prioritize shorter commutes when they choose where to live and work, then estimates of commute effects are biased—commute effects mix with the impacts of commitment to work. In the labor market context, Xiao, Wu, and Kim (2021) show that increased commuting time decreases worker productivity by using firm relocations as shocks to inventors' commutes and measuring their ensuing patent output.[1] Because it is uncommon to observe exogenous changes in commute alongside clear measures of individual output, no other known studies have estimated the causal relationship between commute length and productivity of workers.

School bus transportation provides a uniquely suitable environment for studying commute effects. Riding the school bus is different than commuting by car or public transit because it is impossible to fully account for school bus routes when choosing where to live. Parents can select housing close to their child's school to allow for walking or easy car commutes. However, if a student rides the bus, living close to the school does not guarantee a short ride. Schools balance competing priorities when they design bus routes. They minimize transportation costs and provide bus service to anyone who requests it. Minimizing costs and providing comprehensive service lead to longer ride times because schools try to operate buses at capacity. This means riders sit through more pickups on each route, lengthening their commutes and weakening the relationship between housing choice and commute. Schools assign short commutes to some students who live far from school but are picked up late in the

[1] Mulalic, Van Ommeren, and Pilegaard (2014) pioneered this approach for isolating commutes from residential sorting, finding that firms compensate their workers with wage increases when commutes increase in response to a firm relocation.

route order, and long commutes to some students who live closer to the school but are picked up early in the route order.[2] Based on this variation, school bus rides are a good context for generating plausibly causal estimates of the impact of commuting on performance.

For this study, I merge student-level administrative transportation records from eight county-wide school districts in North Carolina (covering roughly 5 percent of the public school students in the state) with student-level academic records. This transportation data gives detailed information on the morning and afternoon commutes for the universe of bus riders in participating districts. Empirically, I isolate the exogenous variation in bus route assignments using route and distance ring fixed effects to restrict my analysis to comparisons between students who ride on the same bus or live a similar distance from their school. Within these groups, I find that longer bus commutes lead to worse attendance, lower test scores in reading and math, and more discipline referrals.

I explore potential mechanisms for these effects by analyzing children's time-use data from the Panel Study of Income Dynamics-Child Development Supplement. I find suggestive evidence that students compensate for long morning commutes by waking up earlier and getting less sleep. Research has shown that early school start times (and the corresponding early wake-up times) negatively impact students.[3] Long morning commutes operate through similar mechanisms and should be considered in any discussion of school start times.

By comparing the student time use results to adults' time use patterns from the American Time Use Survey, I consider whether the effects of commuting time on students are likely to apply to adult workers. Adults respond to longer commutes by reducing leisure time more than their younger counterparts, but they also reduce their sleeping time to compensate for the added constraint on their time. If lost sleep is the primary mechanism that makes commutes harmful to students, my results indicate that adults face similar effects from their commutes.

This study contributes to a growing literature on student commutes. There have been several attempts to identify the impacts of school bus rides without student-level ridership information. Edwards (2022) compares outcomes based on students' bus eligibility rather than their bus takeup and finds positive effects on attendance from being just eligible for busing based on home-to-school distance. Gottfried, Ozuna, and Kirksey (2021) compare

[2]Parents are unlikely to respond to unlucky bus routes by changing their housing location. As the student population in a school changes each year, bus routes change accordingly, so even a very attentive parent cannot observe bus routes and use that information to make reliable predictions about future route assignments.

[3]Many studies have documented negative impacts of early school start times for older students including Carrell, Maghakian, and West (2011), Edwards (2012), and Groen and Pabilonia (2019). These findings are closely tied to the physiology literature on circadian rhythms and changes to the natural sleep schedule during adolescence. (Cardinali 2008; Crowley, Acebo, and Carskadon 2007) See Section 2.1 for further discussion.

rural kindergartners who ride the bus with those who do not ride, finding that riders miss fewer days of school. Austin, Heutel, and Kreisman (2019) find that school bus emissions can negatively impact students' health by analyzing bus engine retrofitting. Students saw improvements in their aerobic capacity and test scores after emission reductions.

Most existing studies considering the intensity of commutes have simulated travel times based on students' addresses, available public transportation schedules, and traffic patterns. Burdick-Will and Stein (2024) and Stein, Burdick-Will, and Grigg (2021) generate commute estimates based on public transit routes in Baltimore and find that students facing transfers along their predicted commute are more likely to be late for school and that students who have difficult commutes are more likely to switch schools, prioritizing schools with easier commutes, rather than schools that they ranked in their initial school choice applications. Blagg, Rosenboom, and Chingos (2018) use similar commute simulations in Washington, D.C., and find that longer commutes correlate with small increases in absenteeism.

Cordes, Rick, and Schwartz (2022) is the first study to estimate the causal impact of a longer bus commute on students' academic outcomes. They use bus route fixed effects to analyze the within-route impacts of long bus rides on student outcomes in grades 3–6. They find that longer rides worsen attendance with no significant change in student test scores. They link transportation records with academic outcomes in New York City, where the average bus ride is 21 minutes and the average home-to-school distance is 2.1 miles.

I provide the first causal estimates of student commute effects in a more generalizable context.[4] There are fewer outside transportation options in rural areas—public transit is unavailable and walking is impossible when students live farther from their schools.[5] These features heavily influence the sorting of students into bus transportation, just 8.3 percent of third through sixth graders ride the bus in New York City, but over 40 percent of students ride the bus in my K-12 sample of districts in rural and suburban North Carolina.[6] There are also fewer school choice options in more sparsely populated areas, so long rides are caused by

[4]The only existing descriptions of rural and suburban bus commutes are from surveys and interviews rather than administrative data. (Ramage and Howley 2018; Howley, Howley, and Shamblen 2001; Jimerson 2007)

[5]Infrastructure design also plays a significant role in the practicality of walking to school in rural areas. The EPA generates a Census block-level walkability index based on intersection density, proximity to transit stops, and diversity of land use, indexing to 20 national quantiles, ranked with 0 as the lowest (index values from 0 to 1 correspond to walkability scores in the 0–5th percentiles) and 20 as the highest (20 represents the 100th percentile). This measure underscores the differences in walking infrastructure between urban and rural areas. The average population-weighted walkability index for the 8 counties in my sample is 5.9 out of 20. Mecklenburg County, which includes Charlotte, has an average index of 10.5.

[6]Figure A1 shows ridership trends over time and by student grade. Over half of students ride the bus in grades 1–8, but ridership decreases as students enter high school, below 50 percent for 9th and 10th graders and below 35 percent for 12th graders.

the distance from homes to the nearest school and idiosyncratic routing considerations,[7] not by the choice to travel to more distant schools for a better academic fit. The rural context also gives me more scope to measure the impacts of the longest bus rides. Average ride times within my sample are almost 50 percent longer than the average ride in New York City.

In addition to my analysis of time use which sheds some light on the mechanisms that drive student commute effects, this is also the first study to separate the impacts of morning and afternoon commutes. I find that negative impacts on students are largely based on longer morning commutes, further supporting the importance of wake-up times and sufficient sleep. To the extent that early wake-up times and lack of sleep contribute to the detrimental impacts of long bus commutes, it is also important to consider older students who are more affected by loss of morning sleep than third through sixth graders. My data allows me to analyze attendance and behavioral impacts for K–12 students, state standardized test scores for students in grades 3–8, and course grades and ACT scores for high school students.

I also contribute to the broader literature on commute effects. Existing causal estimates of commute effects in the labor market are limited to rare events (firm relocations) in a specific field where it is possible to isolate individual productivity (inventing). I address these limitations by studying a larger segment of the population—my sample includes almost half of public school students in participating districts. Because of this coverage, my results show that people of wide-ranging ability levels and backgrounds are impacted by their commutes. Time use analysis shows that my results for students can reasonably speak to adult commute effects.

The rest of the paper proceeds as follows. First, Section 2 outlines the bus route design process and a conceptual framework for the impacts of commuting on students. Section 3 describes the transportation records and academic outcomes data used in this study. Section 4 presents my empirical approach for estimating commute effects. Section 5 reports the results, including an analysis of mechanisms based on time use data and a policy counterfactual comparing the costs and benefits of adding an additional school bus at the average school in my sample. Finally, Section 6 concludes.

2 Conceptual Framework

For any commuter, traveling to work or school detrimentally impacts performance in two ways. First, more time commuting means less time for other productive (or productivity-

[7]Ellegood, Riley, and Berg (2024) show that rural districts spend 40 percent more per student on transportation than urban districts, so the financial considerations that drive variation in routing could be more salient when designing routes in rural areas.

enhancing) activities. Second, the commute experience may have impacts that last into the workday or school day.

2.1 Effects of Fatigue and Leisure Crowd Out

More time commuting necessarily leads to less time for other daily activities. For workers, time is substituted away from hours worked, leisure, or sleep. Other time uses, such as household chores, errands, personal care, and time supervising children, are less flexible. Students cannot adjust their working time because school schedules do not change based on commuting times. In Section 5.5 I show that adults and students substitute nearly all of their commute time away from sleep and leisure, suggesting that the time spent on other daily activities remains relatively constant when faced with longer commutes.

It is well-documented that sleep deprivation is associated with worse memory and lower academic performance (Curcio, Ferrara, and De Gennaro 2006; Hershner and Chervin 2014; Dewald et al. 2010; Wolfson and Carskadon 2003), so if students and workers sleep less when faced with longer commutes, the resulting fatigue impacts their productivity. A growing body of literature in economics uses variation in sunset times and experimental interventions to measure the impacts of changes in sleep on productivity. Interventions that increase sleep improve performance, while sleep deprivation worsens both short- and long-term outcomes. (Jagnani 2024; Jin and Ziebarth 2020; Gibson and Shrader 2018; Giuntella, Saccardo, and Sadoff 2024) For students, lost sleep could influence test scores due to fatigue on test day[8] or from the cumulative effect of daily fatigue on learning throughout the school year.

Pope (2016) finds that afternoon math and English classes cause students to earn lower grades and standardized test scores in those subjects compared to their peers who study math and English earlier in the day. Long bus commutes could impact students similarly to having key classes late in the day. In particular, loss of sleep driven by early bus pickups could lead to drowsiness, diminishing students' ability to focus and engage with their coursework.

Early school start times harm older students' academic performance (Edwards 2012; Carrell, Maghakian, and West 2011; Groen and Pabilonia 2019) because changes to circadian rhythms during adolescence make it difficult for teens to wake up early. (Cardinali 2008; Crowley, Acebo, and Carskadon 2007) This suggests that long morning bus commutes are particularly harmful to older students. Students with longer morning commutes face an earlier start to the day than their classmates with more advantageous commutes. Even if stu-

[8] Having a longer commute means that students effectively have a longer school day. Cognitive fatigue decreases within-day performance in many contexts, from standardized test scores to healthcare. (Reyes 2023; Chan, Cohen, and Spiegel 2009; Linder et al. 2014; Archsmith et al. 2021; Hirshleifer et al. 2019; Sievertsen, Gino, and Piovesan 2016)

dents balance earlier wake-ups with earlier bedtimes to neutralize the impacts of commuting on their overall sleep, they could still face fatigue from disrupting their natural schedules.

Relative to morning commutes, afternoon commutes likely have less direct impact on sleeping time. However, afternoon bus rides can inhibit students' participation in organized after-school activities, studying and homework, or leisure time. Even when commutes crowd out activities that are not conventionally productive, reallocating time from leisure to commuting may impact job performance or success at school. In the labor market, Ross and Zenou (2008) show theoretically that when leisure time and shirking at work are substitutes, a longer commute leads to lower productivity.[9] For students, lost leisure time could contribute to burnout or lack of focus in the classroom.

2.2 School Bus Specific Factors

Beyond the opportunity costs of commuting, within-commute experiences can impact students. Commuting on the school bus is a unique experience relative to conventional commutes in a personal car or public transit because students are repeatedly put in an enclosed space with a consistent group of peers. Lenard and Silliman (2024) find that forced social connections on the bus generate academic peer effects. Ideally, commuting with the same people every day would lead to positive socializing; however, there is also evidence of violence and bullying on the bus which could spill over into the school day or dissuade bus riders from coming to school. (deLara 2008; Raskauskas 2005) In student outcomes data, I observe suspensions from misbehavior on the bus, further validating behavioral concerns.

3 Data

This study links two administrative data sources to explore the impacts of bus commutes on students' academic outcomes. First, I observe the details of bus commutes from North Carolina's Transportation Information Management System for the universe of bus riders from eight rural and suburban school districts. I merge these transportation records with student-level education records from the North Carolina Education Research Data Center.

3.1 Transportation Information Management System (TIMS)

Since 1992, North Carolina has required schools to use bus routing software to draw optimized routes and record student-level transportation data through the Transportation Information

[9] Van Ommeren and Gutiérrez-i-Puigarnau (2011) use absenteeism to measure shirking behavior and find that longer commutes lead to more absenteeism.

Management System.[10] Districts are not required to prioritize any specific outcome when designing their routes, but in practice, student safety (minimizing street crossing), cost efficiency (minimizing total miles driven), and the worst commutes (minimizing the length of the longest rides) are frequently considered. Implementing this software system forces districts to keep consistent digitized transportation records. This is particularly impactful for data availability in rural areas. In other states, rural districts are far less likely to record their routes and ride times. These records are used by state administrators to determine the amount of state transportation funding granted to each district for the following year, so data quality is monitored.

Eight out of the 115 school districts in North Carolina shared their TIMS data for this study. During the 2021-22 school year, these districts enrolled about 77,000 students—about 5 percent of public school students in the state. Within the National Center for Education Statistics locale classification system, these districts cover a variety of local contexts, from rural to suburban.[11] The sample runs from 2010-2022 school years, and each annual observation represents a snapshot of the busing situation from a single day in November.[12] Because routes are generally assigned in the fall for the entire school year, these routes should be representative of each student's commute for the whole year. I drop fall 2019–spring 2021 transportation data from all analyses due to the COVID-19 pandemic's impact on school schedules, bus provision, and data reliability.

Records from TIMS provide a relatively complete picture of each rider's bus commute. I observe which students ride each bus through school bus IDs. TIMS also records ride times for the morning and afternoon commutes in minutes, pickup and drop-off times, distance from home to bus stop, and home-to-school distance based on the shortest available walking path.

[10]NC G.S.115C-240(d): https://www.ncleg.gov/enactedlegislation/statutes/html/bysection/chapter_115c/gs_115c-240.html

[11]My analysis consists of 2 Rural: Distant districts, 3 Rural: Fringe districts, 1 Town: Distant district, 1 Suburb: Midsize district, and 1 Suburb: Large district. For definitions of these categories, see here: https://nces.ed.gov/surveys/annualreports/topical-studies/locale/definitions

[12]Because I do not observe daily bus attendance, I identify the impacts of assigned commutes on student outcomes. It is possible that when students get worse commute assignments on the bus, they do not ride the bus. In that case, I assume that students find a more beneficial mode of transportation compared to their assigned bus route, muting any negative commute effects that would have occurred from their initial transportation assignment. Because the route snapshots are from November, districts have time to adjust routes to remove students who never ride on their assigned routes, alleviating concerns about the extreme case. Still, the results in Section 5 estimate a lower bound due to the potential impact of low bus attendance for those with long route assignments.

3.1.1 Characteristics of Rural and Suburban School Bus Rides

My sample includes all bus riders from participating districts from 2010 to 2022—over 500,000 student-year bus ride observations from over 150,000 students. For the 315,000 observations in the final analysis sample for attendance effects, students live an average of 4.95 miles from their school and ride the bus for 30.0 minutes in the morning and 30.8 minutes in the afternoon.

Figures 1–3 plot the distribution of morning ride times, pickup times, and home-to-school walking distances. The distribution of pickup times underscores the importance of accounting for commutes when discussing early school start times.[13] Even if school starts after 8:00 AM, students leave their houses much earlier to board the bus. In these sparsely populated areas, the distributions of ride times and pickup times both have long tails—some students board the bus before 5:30 AM and many ride for over 90 minutes each morning. Figure A4 splits the distribution of ride times by student age. Most districts have fewer high schools than elementary and middle schools, so older students have longer bus commutes—over 10 percent of high school bus riders commute for at least 65 minutes each morning. If early wake-up times harm teenage students, these commutes worsen academic performance.

Consistent with survey-based studies and narratives in the popular press, rural bus commutes are more cumbersome than urban commutes.[14] Compared to the New York City sample from Cordes, Rick, and Schwartz (2022), the average bus ride in my sample takes 38 percent longer and the average student lives 2.4 times farther from their school building by walking distance. Sparser rural populations and lower overall enrollment mean that buses cover significantly more territory. For this analysis, having longer, less direct bus routes is useful because logistical constraints force more students' commutes to deviate from the fastest direct path to the school. This further weakens the connection between housing choice and bus commuting time.

3.2 North Carolina Education Research Data Center (NCERDC)

The North Carolina Education Research Data Center maintains academic records for all public school students in the state. Through de-identified student ID numbers, I link 92 percent of bus records in participating districts to the corresponding student's academic information from the NCERDC.

I observe test scores, grades, attendance, behavior, and student demographics in this

[13] Figures A2 and A3 show that these distributions look quite similar for afternoon commutes, with some students dropped off at home as late as 5:00 PM.

[14] New Orleans is an exception to this trend. Lincove and Valant (2018) find that the median bus rider commutes for 35 minutes in a city where relatively few students attend their neighborhood school.

data.[15] I construct behavior and attendance indicators from data on suspensions and absences. Based on the reasons for each suspension, I can separate the impacts of commuting time on bus-related and non-bus-related suspensions for each student. Test scores on 3rd–8th grade end-of-grade exams in math and reading and ACT composite scores are my primary measures of a student's academic performance. Finally, I estimate the impacts of commute length on students' high school grade averages.

3.2.1 Characteristics of Bus Riders

While ridership rates in North Carolina dictate that bus riders represent a relatively broad subset of the total distribution of students, each student still chooses whether or not to ride the bus based on the transportation options available to them. Table 1 details the characteristics of bus riders (defined as those assigned to a bus route in November) compared to students who used other modes of transportation during the 2021–2022 school year. The differences between bus riders and non-riders are stark. Relative to non-riders, riders are less likely to be white, are more economically disadvantaged, and are more likely to be English Language Learners. On average, bus riders are suspended 55 percent more often and score notably worse on standardized tests. These trends indicate that a relatively disadvantaged group of students commutes by bus.

For my analysis, I only compare bus riders to other bus riders, so the validity of the estimates does not rely on similarity between the set of students who ride the bus to school and those who do not. However, it may be concerning if students with longer bus ride times exhibit systematically different characteristics than students with short rides. Table A1 divides 2021–2022 bus riders into those who ride for less than 30 minutes, 30–45 minutes, 45–60 minutes, and more than 60 minutes. The demographic composition of students with long bus rides is relatively consistent with the composition of students with short rides. It is more difficult to interpret any differences in academic outcomes for riders who fall into different time bins because commuting time could impact these outcomes.

Table A2 tests for covariate balance more formally. Columns (1) and (3) present the unconditional relationship between student characteristics and their AM bus ride times and the relationship conditional on their home-to-school walking distance, respectively. Black and Hispanic students seem to have shorter commutes, while economically disadvantaged students have longer commutes. Columns (2) and (4) show the within-bus-route relationships between student characteristics and commuting time. Here, the relationship between demographics and commuting assignments weakens significantly. Accounting for home-to-school distance and including bus route fixed effects, Black students have 0.5-minute shorter

[15] Attendance data is missing from NCERDC records for the 2019-20 school year.

commutes and economically disadvantaged students have 1-minute longer commutes, with no significant relationship between ride times and being Hispanic or female. Still, I control for race, gender, and socioeconomic status in all of my main specifications.

3.3 Sample Selection and Variable Definitions

I restrict my final analysis sample to students who appear in the main attendance panel with a positive attendance rate and in my panel of bus rides with positive morning and afternoon ride times. Some students only ride the bus in the morning or afternoon, but not both. When students only utilize the bus for one of their two daily commutes, I remove them from the main analysis because I cannot fully characterize their daily travel. During the 2021-2022 school year, only 2.9 percent of bus riders had one-way bus assignments.[16] I additionally require that students have non-missing sex, race, English Learner status, economically disadvantaged status, academically or intellectually gifted status, and disability status.

For all test score outcomes, I standardize across the universe of scores in North Carolina by test, grade, and year. This allows me to interpret testing results in standard deviation units. I construct each high school student's overall grade average from their final percentage grades across all available GPA-eligible high school courses for each academic year.[17] Finally, I define a student as ever suspended within a given academic year if they receive any out-of-school or in-school suspension during that year. I assume all students who appear in the attendance panel but do not appear in the suspension records have zero suspensions.

3.3.1 Separation of Morning and Afternoon Commutes

I define two main treatment variables, morning commuting time in hours and afternoon commuting time in hours. Students' morning bus ride times can be correlated with their afternoon commutes, but they vary considerably for some students. These variations can result from equity concerns within the route design process. One option is for schools to run their morning and afternoon routes in the same order. This way, the first student to board the bus in the morning (the student with the longest ride) becomes the first student to exit the bus in the afternoon (giving them the shortest ride), and vice versa. When schools

[16] On average, students with a one-way commute assignment are slightly more likely to be white and less likely to be economically disadvantaged. They also score higher than two-way bus commuters on standardized tests.

[17] When letter grades are reported, I base the percentage grade on the midpoint of the percentage range that would lead to the reported letter grade, accounting for the shift in statewide grading scale that began in the 2015–16 school year. https://www.wunc.org/education/2014-10-02/nc-high-schools-moving-to-10-point-grading-scale

design their bus schedule this way, half of the students get longer morning commutes while the other half get longer afternoon commutes. If every student rode in the morning and afternoon, all students would end up with the same average commuting time across the two bus rides. If schools run their morning routes in the opposite direction of their afternoon routes, then morning and afternoon ride times are more positively correlated—the students with the longest morning rides also have the longest afternoon rides.

Because of the relationship between morning and afternoon commutes, interpreting the magnitude of commute effects based solely on morning commutes is difficult. With variation arising from the scheduling strategy described above—or from routing changes necessitated by differences in morning and afternoon ridership—I separately identify the impacts of morning and afternoon commutes. To do this, I include two ride time terms within each specification, one for the morning and one for the afternoon. I recover separate morning and afternoon commute effects, conditional on the length of the opposite commute.

4 Empirical Approach

Endogenous housing choices threaten the identification of commute effects. In the context of school commutes, one way this could bias estimates is if parents choose their housing location based on the nature of their student's commute to school. If more-engaged parents choose homes closer to the school or secure convenient commutes, estimates overstate the relationship between commuting time and student achievement. The effects of less parental engagement exaggerate the impacts of commute length.

Because school commutes by public transportation or personal car are predictable based on stable routes and traffic patterns, they are likely to factor into the location decision of a family that perceives negative impacts from commutes. However, when students commute on the school bus, their home-to-school distance is less strongly correlated with the time it takes them to get to school. Instead, idiosyncratic bus routing decisions determine the length of their commutes.

Each year, districts in North Carolina must provide transportation to any student who requests it and lives more than 1.5 miles from their school with broad discretion over their routing approach.[18] In particular, transportation administrators have noted that they prioritize safety (minimizing street crossings to get to bus stops), minimizing total miles driven for the entire bus fleet, minimizing the total time of each route, minimizing the number of

[18]Districts are required to provide a bus stop within one mile of the residence of each eligible student who requests transportation, but in practice, almost 90 percent of riders in my sample districts board at a bus stop within 0.25 miles of their home.

students riding for over one hour, and equitably assigning total commuting time for each student (through first on the bus in the morning/first off the bus in the afternoon, etc.). In North Carolina, districts are reimbursed for past year's realized transportation expenses with a budget rating multiplier that penalizes districts when they do not transport students efficiently.[19] The breadth of these considerations means that even route design options that lead to similar average ride times, or assign students to the same routes while optimizing route order, can lead to substantially different commutes at the student level.[20] Finally, after determining which students will be on each bus and which order they will optimally be picked up, districts have the flexibility to run these routes in the reverse order (switching which students are the early versus late pickups) without any change in the route's attributes (conditional on traveling on two-way roads, etc.).

Even if parents were very attuned to a school's bus routing decisions for one year, they could not necessarily leverage that information in the housing market for the following year because routes are redrawn each school year, and even relatively small changes in the student population could substantially alter the optimal route design.

If variation in bus route assignments fully separates commuting length from housing choice, the following simple model uncovers commute effects.

$$Y_{it} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \delta_t + \mu_g + u_{it} \tag{1}$$

Here, Y_{it} is a student outcome variable (attendance rate, suspension record, grade average, or standardized test scores). $RideTime_{it}$ is a vector containing $AMRideTime_{it}$ and $PMRideTime_{it}$, defined as the time spent on the bus each morning and each afternoon for student i in year t, respectively. X_{it} is a vector of student-level controls including sex, race, income level, gifted status, and English Language Learner status. δ_t and μ_g are year and grade-by-school fixed effects. These fixed effects control for any year-to-year variation in the overall relationship between bus ride times and student outcomes and any time-constant differences in commuting between grades within a school and between schools.

I further isolate the idiosyncratic variation in commuting time from any residual variation driven by housing selection in augmented specifications. First, I control for home-to-school walking distance for each student. Then, I use bus route fixed effects to restrict comparisons to students with varied commutes whose families made similar housing and school choices.

[19] North Carolina defines the budget rating based on a district's cost per transported student and number of buses per 100 transported students, conditional on site characteristics including student distance from school, density of students, and transportation requirements for Early College students.

[20] See Appendix C for a simulated example of one approach to route optimization based on minimizing miles driven, minimizing average ride time, or minimizing the longest ride time.

4.1 Bus Route Fixed Effects

Neighborhoods significantly impact students' long-run outcomes and educational attainment. (Altonji and Mansfield 2018; Laliberté 2021) When differences in home neighborhood determine commuting time, estimating commute effects is difficult. Following Cordes, Rick, and Schwartz (2022), I use bus route fixed effects to correct for confounding variation in school choice decisions and housing location. This approach is particularly compelling when bus routes travel into a neighborhood, pick up all the students from that neighborhood, and return to the school. This way, I restrict comparisons to students from families with similar housing choices.

Specifically, I estimate the following specification:

$$Y_{it} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \lambda SchDist_{it} + \omega_r + \delta_t + \mu_g + u_{it} \tag{2}$$

I define a bus route fixed effect, ω_r, for students on bus route r based on bus route identifiers provided in the TIMS records.

Figure 4 provides an example of bus route design from TIMS. Each bus route travels away from the school in a different direction, circles that area, and returns to the school building. This common route structure provides substantial variation in the length of rides for students who live in the same direction from the centrally-located school building. For example, the third and tenth pickup locations along the green route are very close together geographically, but being picked up third leads to a much longer commute as students have to travel around a lengthy loop before heading toward the school. In contrast, students picked up at the tenth location along the route travel directly to the school.

One drawback of within-bus-route comparisons is that they allow for comparisons between students living close to the school and students living relatively far away who ride the same bus to school. To account for remaining differences in housing selection, I control for home-to-school walking distance, $SchDist_{it}$. With this distance control, I measure effects relative to other students riding the same bus, conditional on the distance from each student's home to their school.

4.2 Alternative Specifications

For robustness, I estimate a series of alternative specifications with results reported in Section 5.4. Each of these specifications has drawbacks relative to the bus route fixed effects approach, largely related to a lack of variation within comparison groups, as shown in Appendix B. Morning ride times vary substantially within bus routes and distance rings, but far less within Census blocks and distance ring-by-bus route groups.

4.2.1 Distance Ring Fixed Effects

If distance from home to school correlates strongly with parents' educational engagement or socioeconomic status, it makes sense to make empirical comparisons only between students who live the same distance from the school. This comparison also corrects for differences in selection into busing based on variations in the desirability of outside transportation options such as walking or biking, which depend heavily on living close to school.

To flexibly control for home-to-school distance, I construct concentric rings around each school building and introduce school-by-distance groups based on home-to-school walking distance in miles. With this construction, I compare students who live 0-to-3 miles from school, 3-to-6 miles from school, and so on, up to 12-to-15 miles from the school. I bin all students who live more than 15 miles from the school into one group. I define a fixed effect, ψ_d, for each distance ring d around a given school in the following specification:

$$Y_{it} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \psi_d + \delta_t + \mu_g + u_{it} \tag{3}$$

The major drawback of this approach is that it allows for comparisons between students who live on opposite sides of the school. This could mean their neighborhoods are different or they face varying commuting constraints. If two students live on opposite sides of the school and fall within the distance ring stretching from $x - 3$ to x miles, they can live up to $2x$ miles apart. Students living 30 miles apart in the 12-to-15-mile distance ring may have selected housing based on very different priorities. Figure B2 shows that there is substantial variation in ride times within distance rings. However, the residuals from a regression of AM ride time on home-to-school distance plotted in Figure B6 suggest that bus route fixed effects do a better job of isolating idiosyncratic variation in ride times than distance ring fixed effects, yielding a residual distribution that is more centered and symmetric.

4.2.2 Bus Route-by-Distance Ring Fixed Effects

While bus route and distance ring fixed effects should significantly reduce the influence of housing choice on the estimation of commute effects, neither perfectly achieves the goal of only comparing the outcomes for students who live close to each other.

Bus route fixed effects control for neighborhood selection, but do not inherently account for distance to school. Distance ring effects flexibly account for distance to school, but not direction from school. Therefore, a natural extension is to interact distance rings with bus routes, restricting comparisons to students who live within the same distance ring and ride the same bus.

Within these distance-by-route groups, variation in ride times is limited (see Figure B3), so I also estimate a less-restrictive model with additive bus route and distance ring fixed effects. This is similar to the bus route fixed effects model with home-to-school distance controls. The additive fixed effects allow for a non-linear relationship between home-to-school distance and commute length.

4.2.3 Census Block Fixed Effects

A more direct approach is to restrict comparisons based on student addresses. To do this, I use Census Block-by-School fixed effects to isolate students who have chosen the same school and live close together. This approach has two key drawbacks in my setting. Figure B4 shows that many Census Blocks have little to no variation in bus ride times compared to bus routes or distance rings. Additionally, the NCERDC only reports student addresses through 2017, so I lose a considerable share of my sample when including Census Block-level addresses in the analysis.

4.2.4 Lagged Outcomes

I re-estimate my main specifications using an augmented model that includes lagged outcomes from the previous school year, $Y_{i,t-1}$. This way, I estimate commute effects on academic outcomes relative to a student's past performance. The downside of controlling for lagged outcomes in this context is that there is often a correlation between last year's commuting time and this year's commuting time, which could lead to an underestimate of the impact of this year's commute. It is also difficult to interpret these estimates if having a long commute has longer-run negative effects that spill over into future school years.

4.2.5 Student Fixed Effects

Based on persistent student IDs, I can estimate with student fixed effects to fully control for differences in underlying characteristics by making only within-student comparisons over time, but this approach has several drawbacks. First, large within-student variation is likely to occur when students move homes or switch schools, which could be endogenous to their academic performance and commute. Second, similar to including lagged outcome variables, student fixed effects estimation relies on bus route effects being contained within a given year rather than accumulating in the long run. Finally, like route-by-distance ring fixed effects, student fixed effects greatly decrease the available variation in ride times as shown in Figure B5.

5 Results

To gain a broad understanding of the effects of commutes on students, I begin by analyzing the impacts of additional commuting time on students' behavior and attendance. Next, I consider the effects of commutes on classroom performance, as measured by high school grades and a range of standardized test scores. I also present effect heterogeneity by student characteristics. To explore the mechanisms that drive commute effects for students and provide suggestive evidence on how these findings may translate to adult commutes, I analyze time use data for students and working adults. Last, I consider the costs and benefits of purchasing and operating an additional school bus to reduce the length of student commutes. While the main treatment variable of interest is commuting time in hours, it is rare to observe a full hour difference in ride times between otherwise similar students. Therefore, I interpret estimates based on a one standard deviation increase in ride time—21.5 minutes for morning commutes and 22.8 minutes for afternoon commutes.[21]

In Tables 2–5, Column 1 presents the results from a model with student demographic controls, but no route fixed effects. Column 2 adds a control for home-to-school walking distance. Column 3 includes bus route fixed effects. Finally, Column 4 shows the estimates for my preferred specification which uses bus route fixed effects and controls for home-to-school walking distance.

5.1 Effects on Behavior and Attendance

First, I consider the impacts of commute length on student behavior. Table 2 shows that a longer school bus ride significantly increases the likelihood of receiving a suspension in a given school year. In particular, a one standard deviation increase in AM ride time leads to a 1.7–2.6 percent increase in suspension. At first glance, there does not appear to be any effect of afternoon commute length on suspension rate. However, the results in the middle and bottom panels of Table 2 show heterogeneity in the influence of morning and afternoon commutes based on the cause of suspensions. The middle panel reports the effects of commute length on suspensions with bus misbehavior listed as a cause. Since more time on the bus gives more time for misbehavior, longer commutes lead to more bus-related

[21] That is, for a better contextualization of magnitudes, estimates in Tables 2–5 and Tables A4–A11 should be scaled down by a factor of 2.8 and 2.6 for morning and afternoon commutes, respectively.

suspensions.

A one standard deviation in morning commuting time leads to a 4.0–9.3 percent increase in bus-related suspensions while a one standard deviation increase in afternoon commuting time leads to an even larger 11.4–17.1 percent increase in bus-related suspensions. On a long morning commute, students are drowsy from their early wake-up times, perhaps diminishing their rate of misbehavior relative to the afternoon commute. The difference in effects between morning and afternoon rides is ever starker for non-bus-related suspensions. The fatigue from longer morning rides leads to increased misbehavior during the school day (a 1.3–2.3 percent increase in non-bus suspensions) while afternoon commuting time reduces the likelihood of having at least one non-bus suspension (a 1.1–2.0 percent decrease). Combined with the large increase in bus-related suspensions, this could indicate that interpersonal conflicts related to the afternoon commute are more likely to be resolved during the bus ride itself instead of spilling into the school day.

Since bus commutes are students' first school engagement in the morning and their last school engagement in the afternoon, they impact students' decisions to attend school. Table 3 reports my main attendance results. The upper panel focuses on the impact of commuting time on annual attendance rates. Across specifications, I find that longer commutes lead to worse attendance. The effect of a one-hour increase in afternoon commute on attendance is about -0.1 percentage points with bus route fixed effects and controlling for home-to-school distance. For a one standard deviation increase in afternoon commute, attendance rates fall by 0.04 percentage points. The average attendance rate is about 94.95 percent, so this is a decrease of less than 0.1 percent in attendance or about a 1 percent increase in the absence rate. In contrast, morning commutes have little impact on attendance rates.

Though these results are of questionable economic significance given the small magnitudes, they provide evidence that ride length impacts attendance decisions. It is worth considering why the effects arise from afternoon commutes. This finding seems counterintuitive because long morning rides lead to early wake-up times, increasing the likelihood of missing the morning bus. One potential explanation is that students choose whether or not to get on the bus based on their last school-affiliated interaction from the previous day—their afternoon commute. Behavioral results on bus-related suspension rates support this story because students with long afternoon routes experience more misbehavior during their commutes.

The lower panel of Table 3 analyzes the impacts of commute length on chronic absenteeism, defined as being absent for over 10 percent of the available school days in a given academic year. The coefficients from specifications with bus route fixed effects (columns 3 and 4) show that increasing the commute length by one standard deviation leads to a 1–2 percent increase in the likelihood of being chronically absent. This means commutes detrimentally impact the attendance rates of students who are already susceptible to missing school.

5.2 Effects on Grades and Test Scores

Given the established influence of early school start times on student testing outcomes (Groen and Pabilonia 2019; Edwards 2012; Carrell, Maghakian, and West 2011), it is likely that long commutes—which similarly force students to wake up earlier in the morning—also impact students' performance on tests. Table 4 shows that having a longer morning commute leads to worse test scores, with no significant impacts from afternoon ride times.[22] Based on the main specifications in columns 4 and 5, a standard deviation longer commute leads to a 0.01 standard deviation decrease in score on the end-of-grade math exam for 3rd–8th-grade students. For end-of-grade reading exams, the effects are smaller and only significant in the naive specification that does not include bus route fixed effects. While these effects are not large in magnitude, they are relatively similar to other estimated effects on test scores that are likely generated by student fatigue.[23]

For high school students, I find slightly stronger effects than for elementary and middle school students—a one standard deviation increase in morning ride time leads to a 0.02 standard deviation decrease in ACT Composite score.[24] Unlike end-of-grade exams, the ACT is not a test of a student's accumulated knowledge from daily coursework in a given year. Instead, the ACT tests students' overall understanding of high school material.[25]

It is unclear whether commutes affect test scores due to fatigue on the day of the test or the cumulative impacts of fatigue on learning throughout the school year. I separate ACT effects by subject—and therefore by section order[26]—looking for varied responses to long commutes throughout the test day. Students take the English and Math sections of the ACT before taking a ten-minute break. Then, they return for the Reading and Science

[22]Using data on school start times from 2011-2016 (Bastian and Fuller 2018), I check for influence of morning waiting time between bus dropoff and the start of the school day. Conditional on commuting time, I find no statistically significant effects on test scores, attendance, or behavior from having a longer wait.

[23]For a one-hour increase in morning commute, I estimate a 0.03sd decline in math scores. Edwards (2012) estimates a 0.06-0.08sd decline in test scores for a one-hour earlier school start time. Pope (2016) estimates a 0.02sd decline in math scores when students are assigned to an afternoon math class instead of a morning math class with no effect on reading scores.

[24]Impacts on HS test scores could indicate greater responsiveness to the early wake-ups in the teenage years. Or, the relatively disadvantaged students who still ride the bus when they are old enough to drive themselves are more sensitive to their commutes.

[25]https://www.act.org/content/act/en/products-and-services/the-act/scores/why-take-the-act.html

[26]https://www.act.org/content/act/en/products-and-services/the-act/test-day.html

sections. Table A3 shows that commute length appears to impact students slightly more strongly during the second half of the test. On the Reading and Science sections, students with longer morning commutes score significantly worse, with no statistically significant impacts on the first two sections of the test or from afternoon commutes. While differential impacts of commute by subject could also explain these results, the lack of effect on the math section does not align with the main end-of-grade testing estimates. Instead, the ACT results suggest test-day fatigue.

Course grades are a less consistent measure of student performance than test scores, but provide an additional indication of student effort and output. Table 5 reports the impacts of commuting time on average grades for high school students across all core classes (math, science, social studies, and English language arts) in the top panel and on average grades in math and science courses in the bottom panel. For core classes, commuting time does not significantly impact grades. However, for math and science classes, there are small, marginally significant, negative impacts of longer afternoon commutes on average grades. Math and science classes may assign more work outside of the school day or require more studying. Therefore, I hypothesize that longer afternoon commutes take up post-school time that would otherwise be spent on homework or studying. Consistent with the idea that these effects arise from time conflict rather than fatigue, there are no significant impacts from morning commuting time on grades. Together, the results on test scores and grades show that students' commuting time impacts their academic performance.

5.3 Heterogeneity

5.3.1 Demographics

Heterogeneous commute effects for different student groups could have implications for tailoring the appropriate policy response to students struggling with their travel to school. Figures A5–A7 plot the effects of morning commuting time separately by student race, sex, and economically disadvantaged status from the main bus route fixed effect specification conditional on home-to-school walking distance. Boys are particularly impacted by their commutes, in line with existing research that finds that boys' behavior and academic performance are more sensitive to family and school inputs. (Autor et al. 2016) For attendance rate, suspension rate, end-of-grade math and reading exams, and the ACT composite score, boys have statistically significant detrimental responses to increased commuting times while the commute effects for girls are statistically indistinguishable from zero. This suggests that the impacts of commuting by bus exacerbate gender gaps in behavior and academic achievement.

By race, I find little evidence of effect heterogeneity. White, Black, and Hispanic students are all more likely to be suspended when faced with a longer morning bus commute. There is weak evidence that Hispanic students are less impacted on 3rd-8th grade end-of-grade exams than White students, but see larger negative impacts on their ACT composite scores.

Students with lower socioeconomic status (those classified as economically disadvantaged) are more likely to be suspended when they have a longer commute while there is no statistically significant impact on non-economically disadvantaged students. Higher SES students with longer commutes counterintuitively have higher attendance rates than their peers with shorter commutes, but lower SES students with longer commutes have statistically significantly lower attendance rates than their peers. This could reflect differences in the reliability of outside transportation options based on income status.[27] Commuting time does not have any statistically significant impact on lower SES students' test scores, but has a negative impact on higher SES students' math test scores and ACT composite scores.

5.3.2 Ride Time

Figures A8 and A9 plot the effects of a longer ride on behavior, attendance, and math and reading test scores by ride time bin. Generally, longer rides seem to lead to worse outcomes, consistent with the main linear specification. However, riding the bus for more than 45 minutes in the morning leads to the largest increase in likelihood of suspension, with no additional impact from traveling for longer than 60 minutes. Additionally, the negative effect of PM commutes on attendance rate is most-evident for riders traveling for more than 60 minutes. While I still observe greater impacts on end-of-grade math test scores than end-of-grade reading test scores, those with the longest morning commutes (more than 60-minutes) see a significant decline in their reading scores as well as their math scores. In shorter commute bins (15-30 minutes, 30-45 minutes), only math scores are significantly lower than for students who ride the bus for less than 15 minutes in the morning. Even for students with the longest afternoon commutes, there is no significant impact on test performance.

5.4 Robustness

Tables A4 through A7 report the estimates from the specifications that control for lagged outcomes. For behavioral outcomes, attendance, grades, and test scores, controlling for lagged outcomes has little impact on the estimated coefficients. Tables A8 through A11

[27] For example, higher income students may skip their assigned bus commute more often if they are assigned a longer ride and get a reliable ride to school in a personal car.

show that using bus route and distance ring fixed effects together yields similar results to the main specifications. With Census Block fixed effects or interacted bus route and distance ring fixed effects, the results are qualitatively similar, but lose statistical significance due to the lack of geocoded address data after 2017 and insufficient variation in morning ride times within fixed effect groups as evidenced by Figures B4 and B3. Similarly, with student fixed effects, the results are quite similar to the main bus route fixed effects specification for suspensions, attendance, and grades, though the impact of AM ride time on math scores is no longer statistically significant.

5.5 Mechanisms: Time Use Analysis

Differences between the impacts of morning and afternoon commuting time on behavior and academic achievement suggest that fatigue drives student commute effects. I use 24-hour time use diaries from the 2014 and 2019 Panel Study of Income Dynamics Child Development Supplements (PSID-CDS) to analyze how students adapt to long commutes.[28] During the school year, children spend many of their weekday hours in class and often spend additional hours studying and completing academic assignments outside the conventional school day. These components of students' days are relatively inflexible, so when kids have longer commutes, they must reduce their time on other non-school activities.

5.5.1 Children's Time Substitution

School and school commutes cut into students' time spent on other activities, including sleeping and exercise. Cowan, Jones, and Swigert (2024) merge school start dates with the American Time Use Survey (ATUS) to show that 15–17-year-old students wake up much earlier during the school year than during the summer, leading to over an hour of lost sleep after school begins in the fall. Speaking directly to the influence of travel time, Voulgaris, Smart, and Taylor (2019) find that 15–19-year-old students with longer school commutes spend less time sleeping and exercising based on the ATUS.

I replicate these results based on time-use diaries from the PSID-CDS for students aged 5–18. It is important to consider children younger than 15 in my context because bus ridership rates are highest before high school, and my main testing sample covers grades 3–8. Figure 5 shows that, among 1,407 students between the 2014 and 2019 PSID-CDS, children with longer morning commutes get less sleep. Figure A10 shows that this relationship is due

[28] Child Development Supplement to the Panel Study of Income Dynamics (2024)

to earlier wake-up times.[29] Conditional on age, sex, year, and family income, students with 30-minute longer commutes wake up 23 minutes earlier in the morning and go to bed just 3 minutes earlier in the evening—a cumulative 20-minute decrease in total sleep.[30] Longer commutes are also associated with decreased time spent on leisure activities such as watching videos, playing video games, reading, and playing outdoors. There is no significant relationship between time spent commuting and time spent studying or doing homework.

While these relationships are correlational rather than causal, they provide suggestive evidence that students' commuting time primarily crowds out sleep. Given the impacts of fatigue on students described in Section 2.1, the loss of sleep explains the negative effects of commutes on academic performance.

5.5.2 Adults' Time Substitution

Xiao, Wu, and Kim (2021) find that longer commutes impact workers' productivity by measuring the impact of commute changes induced by firm relocations on inventors' patent production and patent quality. In general, there are few exogenous sources of commute variation for adults as public transit routes are known in advance and adults often commute by personal car.[31] Additionally, data on individual-level productivity is scarce. By analyzing commutes in the school context, I overcome these limitations. Schools design bus routes by making idiosyncratic decisions based on multiple competing goals. These logistical considerations separate commute length from residential location for students who ride the bus. Student-level academic records offer detailed information about students' behavior and performance.

To judge whether these results are likely to translate from children to adults, I analyze the impacts of commuting time on adult time use with time diaries from the American Time Use Survey (ATUS).[32] I restrict to non-holiday Monday–Thursday commutes from home to work and limit the sample to non-students. From 2003–2023 time diaries, I analyze 10,572 morning commuters. Table 6 shows that, when adults have a 30-minute longer commute, they sleep 12 minutes less and have 18 minutes less leisure time. If I take the suggestive time use analysis literally and sleep loss accounts entirely for commute effects, I would expect adults to face about half of the detrimental impacts of long commutes compared to students.

[29] Figures A11–A13 plot this relationship by student age. Elementary and middle schoolers respond similarly to long commutes, but high schoolers adjust for early wake-up times with earlier bedtimes, reducing the amount of overall sleep loss.

[30] Similarly, a one hour delay in school start time leads to 38 minutes more sleep for female students. (Groen and Pabilonia 2019)

[31] For teachers, having a long commute is associated with higher turnover rates, increased absenteeism, and lower evaluation scores. (Santelli and Grissom 2024)

[32] U.S. Bureau of Labor Statistics (2024)

This rough estimate may undersell the impact of commuting time on working adults because they consume substantially less leisure time when faced with long commutes. I define leisure time as any time spent in two ATUS categories: Socializing, Relaxing, and Leisure and Sports, Exercise, and Recreation. A lack of leisure time could lead to decreased effort at work if shirking is a substitute for leisure. (Ross and Zenou 2008) Crowding out of exercise and other physical activities could also result in health impacts from commuting. (Künn-Nelen 2016; Clark et al. 2020; Gimenez-Nadal and Molina 2019) Bencsik, Lusher, and Taylor (2025) find that when car commuters face more congested traffic, they are more likely to eat fast food which could also impact worker health. If commutes indirectly harm the well-being of workers, then this likely also impacts productivity at work.[33]

Of course, adults could respond differently than children to long commutes for many reasons. First, adult commutes are not subject to the same behavioral dynamics as students commuting in large, consistent groups of their peers. If attendance effects arise because students experience misbehavior on their afternoon commutes, then adults would not see similar impacts on work attendance.[34] Finally, adults may be more responsible with their time, finding alternative time use substitutions to protect their overall sleep. Adults should also feel fewer effects from early wake-up times than teenagers due to their Circadian rhythms, which naturally support earlier wake-ups compared to high school students.

5.6 Policy Option: Cost/Benefit of an Additional School Bus

Longer commutes harm students' performance in school, which could have long-run consequences. Here, I consider the impacts of a simple policy intervention to reduce student commuting time—purchasing and operating one additional school bus at the average school in my sample.

5.6.1 Assumptions

I cannot observe any post-graduation outcomes for the students in my sample, so I must rely on assumptions about the relationship between school outcomes and longer-run outcomes for students to estimate the benefits of reduced commuting time. I begin by constructing an estimate of the impact of test scores on future earnings based on the existing literature.

Chetty, Friedman, and Rockoff (2014) find that a one standard deviation increase in teacher quality causes a 1.34 percent increase in lifetime earnings from a present value of

[33] In Australia, Ma and Ye (2019) find that actively commuting on foot or by bike is associated with improved job performance.

[34] Van Ommeren and Gutiérrez-i-Puigarnau (2011) find that workers with longer commutes are more likely to be absent from work, using worker fixed effects to isolate commute changes.

$522,000 at age 12, assuming a 5 percent discount rate. Rockoff (2004) finds that a one standard deviation increase in teacher quality causes a 0.1 standard deviation increase in student test scores. Assuming the effects of teacher quality are fully captured by student test scores, a 0.1 standard deviation increase in test scores leads to a 1.34 percent increase in lifetime earnings. Commuting time is not nearly as impactful as teacher quality—a one standard deviation increase in commuting time causes students to score 0.01 to 0.02 standard deviations lower on standardized tests. Still, increasing commuting time by 21 minutes would lead to a 0.134 to 0.268 percent decrease in lifetime earnings—$700 to $1400 per student.

5.6.2 Calculation of Costs and Benefits

To obtain and operate an additional bus, schools take on costs. First, a Type C diesel school bus costs about $90,000.[35] According to the Bureau of Labor Statistics, the average school bus driver makes $21.74 per hour, corresponding to about $16,000 during a 37-week school year for a driver who works 20 hours per week. It also costs about $6,000 per year to fuel a school bus.[36] Finally, bus maintenance costs average about $15,000 per year, per bus.[37] Diesel school buses have lifespans ranging from 12–15 years. Accounting for the cost of the initial purchase and operating the bus for 15 years, with a 5 percent discount rate, the present value of the lifetime cost of a new school bus is $493,250.[38]

All bus riders at a school benefit from decreased commuting time when a school adds a bus, not just the riders assigned to that bus. In my sample, the average school transports 326 students per year on 9.5 buses (an average of 34.3 students per bus). Over the 15-year lifetime of a new school bus, 4,890 rider-year bus rides are shortened in the average district. If one year with a one standard deviation decrease in bus ride increases each student's future earnings by $700 to $1400, shortening the average bus ride by one standard deviation increases the present value of total future earnings for all bus riders at the school by $2.5–5.1 million. Adding one school bus will not decrease average ride time by 21 minutes, but the total future benefits to students equal the total cost to the school if the average ride time

[35] See the following example of 2022 bus purchases from Arkansas. https://www.transform.ar.gov/wp-content/uploads/2020/12/2022-Contract-At-A-Glance-Final.pdf

[36] Estimates of fuel cost are taken from the NC Department of Public Instruction's NC Community Fuel Savings Calculator https://www.ncbussafety.org/fuelcalculator.html

[37] One Michigan district with 9 buses has 1 mechanic paid about $75,000 in salary and benefits and spent $6,100 per bus per year on parts and maintenance costs for an average cost of $14,529. https://www.msbo.org/sites/default/files/BusLeasingCost-2011.pdf

[38] Simulations of the current state transportation funding formula suggest that sample districts could lose about 5-10% of their annual transportation grant due to worsening budget ratings driven by the addition of one new school bus per school in the district. https://www.ncbussafety.org/simulator.html However, there could potentially be scope for lessening this effect through re-allocation of available buses between schools within a district or prioritization of new bus purchases for certain schools.

declines by 0.1–0.2 standard deviations or 2.2–4.4 minutes. Based on route optimization simulations described in Appendix C, the average school in my sample could reduce average ride time by 1.3–4.9 minutes by adding another school bus. This suggests that the future benefits of an additional bus for students could outweigh the costs to the district.

6 Conclusion

Most public school students in North Carolina commute to school on school-provided buses. In rural areas where students are geographically dispersed, these commutes travel along indirect routes as schools minimize costs and maximize their state transportation funding by filling their buses to capacity before returning to the school building. Using administrative transportation records from eight county-wide districts in rural and suburban North Carolina, I show that longer commutes harm students, leading to worse attendance rates, more suspensions, and lower test scores. Morning commutes and afternoon commutes have distinct effects on students. Morning commutes have more impact on non-bus-related suspensions and test scores, suggesting that the morning commute leads to fatigue, which spills over into the school day. Longer afternoon commutes lead to more suspensions for bus misbehavior and worse attendance rates.

Early bus pickups are a missing dimension of the policy discussion surrounding school start times. Analysis of children's time use diaries suggests that students respond to longer commutes by waking up earlier and getting less sleep, similar to their responses to an early school start. Given this substitution between commuting and sleeping time, fatigue likely drives commute effects. Adults make similar time use substitutions to students when they are faced with longer commutes, providing some evidence that negative commute effects on students imply the existence of negative commute effects on adults' effort and productivity.

One potential policy response to long student commutes is to add additional buses to reduce the number of pickups on each route. A simple back-of-the-envelope calculation indicates that the overall long-run benefits to students may outweigh the costs of adding a school bus for the average school in my sample.

My findings also inform the optimal design of transportation funding formulas. In many states (including North Carolina), transportation funding determinations include an efficiency component that incentivizes schools to run their buses at capacity, increasing the number of pickups on each route and increasing average ride times. Given the negative impacts of long commutes on students, this prioritization could reduce transportation costs and increase transportation funding at the expense of student achievement.

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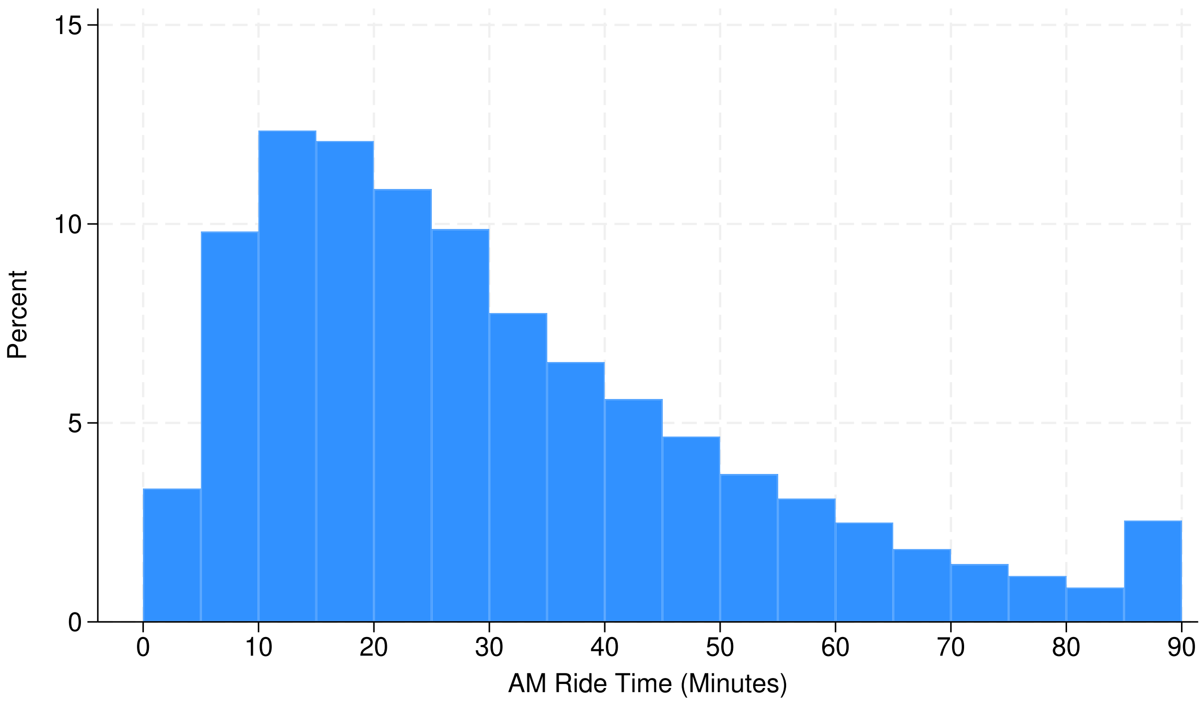
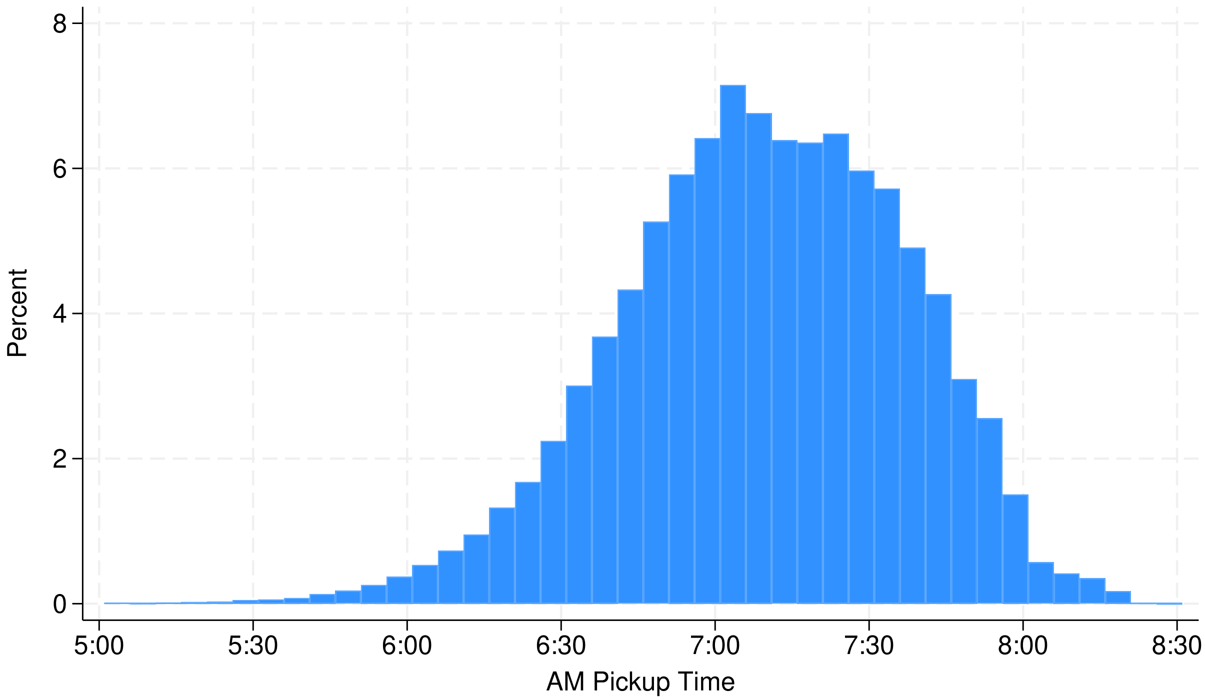
Figure 1: Characteristics of AM Bus Rides



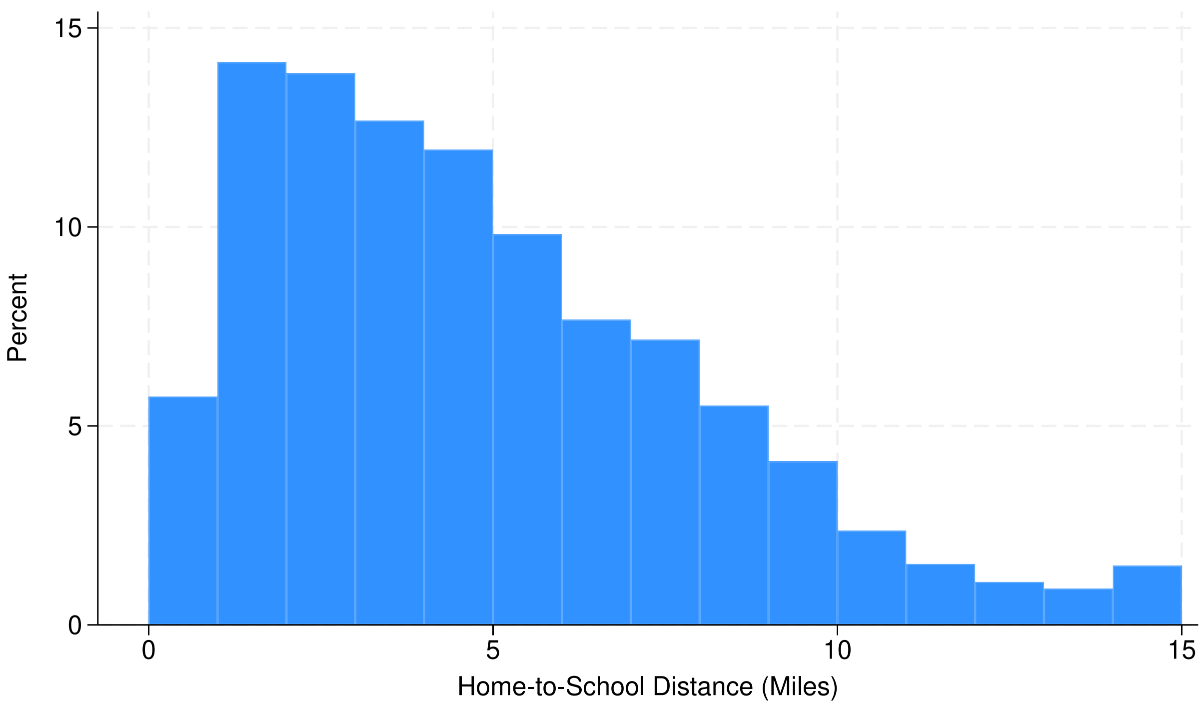
Percent calculated based on observations with non-missing attendance rates, race, and sex. Ride times longer than 90 minutes are binned to 90.

Figure 2: Characteristics of AM Bus Rides



Percents calculated based on observations with non-missing attendance rates, race, and sex.

Figure 3: Characteristics of AM Bus Rides



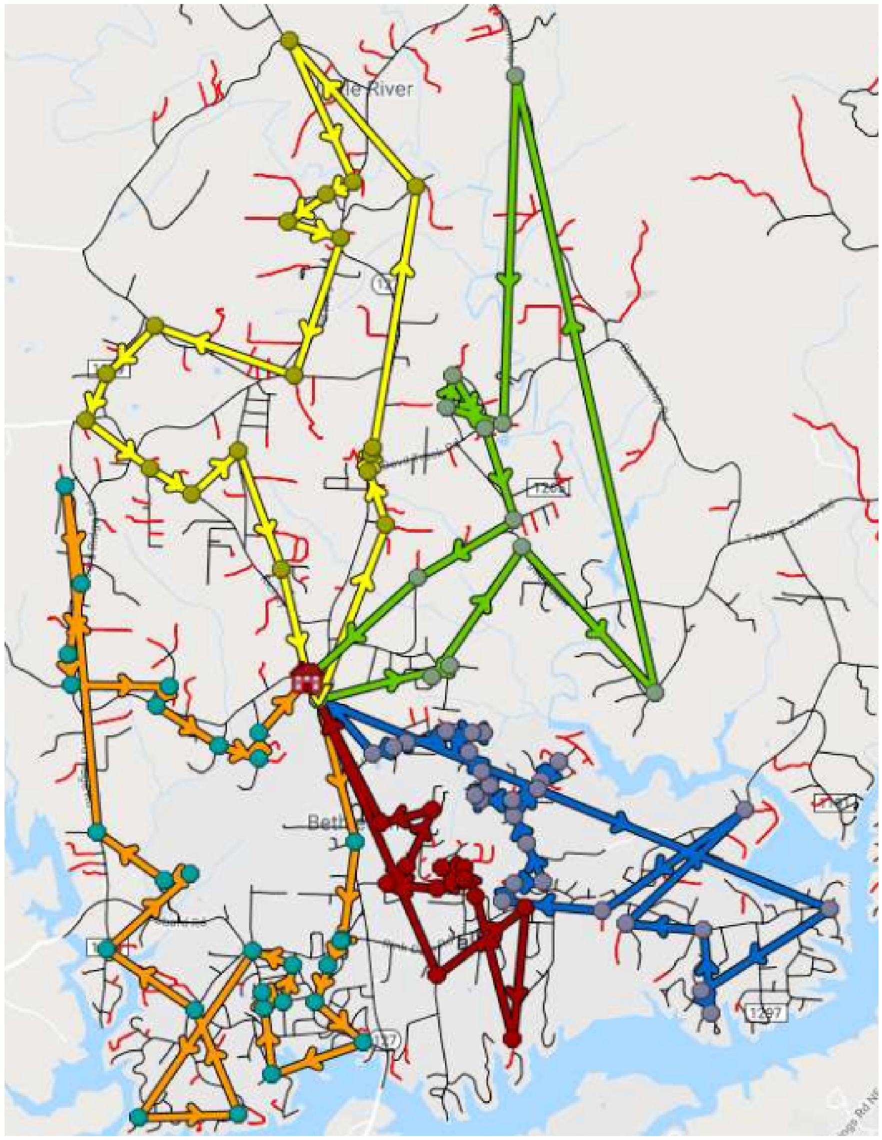
Percents calculated based on observations with non-missing attendance rates, race, and sex. Home-to-school distances greater than 15 miles are binned at 15.

Table 1: Characteristics of Bus Riders and Non-Riders, 2021–22 School Year

	Riders			Non-Riders		
	Mean	SD	N	Mean	SD	N
Race						
Asian	0.01	0.08	31,614	0.01	0.09	46,434
Black	0.15	0.36	31,614	0.10	0.30	46,434
Hispanic	0.31	0.46	31,614	0.21	0.41	46,434
White	0.48	0.50	31,614	0.63	0.48	46,434
Sex						
Female	0.47	0.50	31,614	0.49	0.50	46,434
Other Student Characteristics						
Gifted Status	0.08	0.27	31,614	0.10	0.30	46,434
Economically Disadvantaged	0.45	0.50	31,614	0.37	0.48	46,434
English Learner	0.14	0.35	31,614	0.08	0.28	46,434
Attendance						
Attendance Rate	90.29	8.86	31,650	90.77	9.37	46,648
Behavior						
Any Suspension	0.17	0.37	31,987	0.11	0.31	46,668
Any OSS	0.10	0.31	31,987	0.06	0.23	46,668
Any Bus-Related Suspension	0.02	0.15	31,987	0.01	0.10	46,668
Test Scores						
End-of-Grade Math Score (Grade 3–8)	-0.04	0.95	16,082	0.10	0.98	16,463
End-of-Grade Reading Score (Grade 3–8)	-0.10	0.96	16,464	0.10	0.99	17,031
End-of-Course Math 1 Score (HS)	0.07	1.00	3,125	0.23	1.04	3,710
End-of-Course Math 3 Score (HS)	0.05	0.99	2,139	0.13	1.02	3,398
End-of-Course Biology Score (HS)	0.08	1.01	2,278	0.20	1.01	3,310
End-of-Course Enlish 2 Score (HS)	-0.19	0.93	2,614	0.05	0.98	3,492
ACT Composite Score	-0.19	0.84	1,991	0.01	0.90	3,376
Grades (HS)						
All Courses	79.83	13.02	9,459	82.69	13.02	14,971
Core Courses	76.60	14.25	9,139	80.04	14.22	14,571
Core Math and Science Courses	75.57	15.26	8,688	79.10	15.14	13,493

Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Suspensions are categorized as bus-related if bus misbehavior is listed as a cause for the suspension. All test scores have been standardized at the test-by-grade-by-year level for the entire state.

Figure 4: Sample Bus Routes from TIMS



This is an example of bus routes in North Carolina from public Transportation Information Management System (TIMS) materials, not from the transportation data used in this study.

Table 2: Behavior Results

	1	2	3	4
	Any Suspension			
AM Ride Time (Hours)	0.008***	0.007**	0.010***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.002	-0.004	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Outcome Mean	0.151	0.151	0.151	0.151
N	296545	296179	295387	295194
	Bus Suspension			
AM Ride Time (Hours)	0.006***	0.003	0.007***	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.011***	0.008***	0.012***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.027	0.027	0.027	0.027
N	296545	296335	295387	295194
	Non-Bus Suspension			
AM Ride Time (Hours)	0.005*	0.006*	0.007**	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.007**	-0.007**	-0.005**	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Outcome Mean	0.137	0.137	0.137	0.137
N	296545	296335	295387	295194
Controls				
Home-to-School Walking Distance		X		X
Fixed Effects				
Bus Route			X	X

I define a student as having a bus suspension within a given academic year if they ever receive out-of-school or in-school suspension during that year with the cause of the suspension listed as bus misbehavior. All other suspensions are classified as non-bus suspensions. All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table 3: Attendance Results

	1	2	3	4
	Attendance Rate			
AM Ride Time (Hours)	-0.166***	-0.082	-0.012	0.018
	(0.050)	(0.052)	(0.048)	(0.050)
PM Ride Time (Hours)	-0.153***	-0.080*	-0.125***	-0.098**
	(0.048)	(0.046)	(0.045)	(0.043)
Outcome Mean	94.948	94.948	94.953	94.953
N	296545	296335	295387	295194
	Chronic Absenteeism			
AM Ride Time (Hours)	0.008***	0.005*	0.001	0.000
	(0.002)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	0.006**	0.003	0.005**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.114	0.114	0.114	0.114
N	296545	296335	295387	295194
Controls				
Home-to-School Walking Distance		X		X
Fixed Effects				
Bus Route			X	X

Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table 4: Testing Results

	1	2	3	4
	End-of-Grade Math (3–8)			
AM Ride Time (Hours)	-0.025**	-0.029***	-0.022*	-0.027**
	(0.011)	(0.011)	(0.011)	(0.012)
PM Ride Time (Hours)	-0.007	-0.011	-0.001	-0.005
	(0.011)	(0.011)	(0.011)	(0.010)
Outcome Mean	0.092	0.092	0.093	0.093
N	111492	111452	111184	111143
	End-of-Grade Reading (3–8)			
AM Ride Time (Hours)	-0.019*	-0.024**	-0.013	-0.015
	(0.011)	(0.011)	(0.010)	(0.011)
PM Ride Time (Hours)	-0.002	-0.005	0.004	0.002
	(0.011)	(0.011)	(0.011)	(0.011)
Outcome Mean	0.096	0.096	0.098	0.098
N	107677	107635	107383	107340
	ACT Composite			
AM Ride Time (Hours)	-0.038**	-0.053***	-0.047*	-0.051*
	(0.019)	(0.018)	(0.024)	(0.026)
PM Ride Time (Hours)	-0.005	-0.018	0.003	-0.002
	(0.021)	(0.023)	(0.031)	(0.032)
Outcome Mean	-0.188	-0.189	-0.199	-0.200
N	11465	11436	11094	11071
Controls				
Home-to-School Walking Distance		X		X
Fixed Effects				
Bus Route			X	X

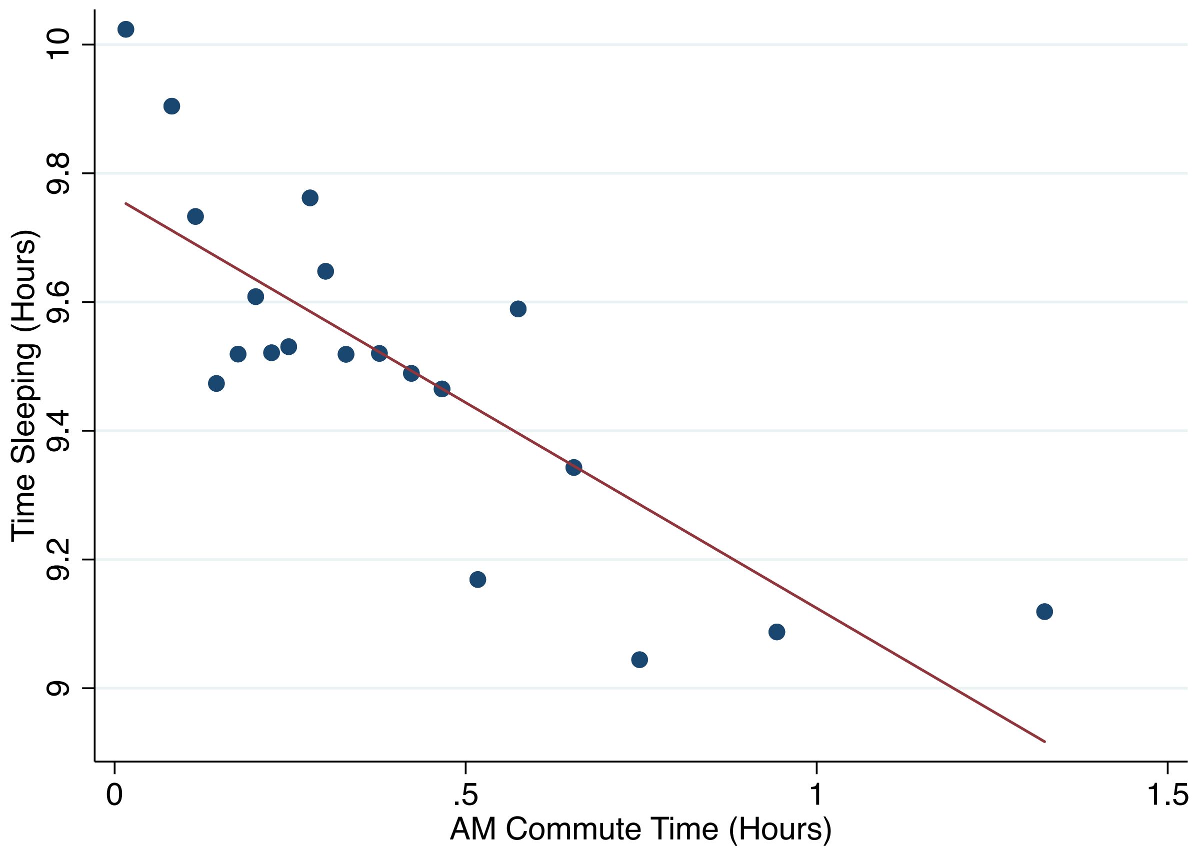
Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table 5: Grade Results

	1	2	3	4
	Core Subject Grades			
AM Ride Time (Hours)	-0.357*	-0.267	-0.181	-0.193
	(0.204)	(0.205)	(0.201)	(0.208)
PM Ride Time (Hours)	-0.394*	-0.317	-0.331	-0.343
	(0.225)	(0.229)	(0.210)	(0.215)
Outcome Mean	80.197	80.193	80.165	80.163
N	87200	87080	86395	86292
	Math and Science Grades			
AM Ride Time (Hours)	-0.310*	-0.191	-0.199	-0.205
	(0.184)	(0.192)	(0.204)	(0.217)
PM Ride Time (Hours)	-0.527**	-0.425*	-0.453*	-0.468*
	(0.238)	(0.249)	(0.240)	(0.252)
Outcome Mean	79.330	79.327	79.294	79.292
N	83753	83640	82990	82893
Controls				
Home-to-School Walking Distance		X		X
Fixed Effects				
Bus Route			X	X

Grades are calculated as the average of all GPA-eligible final grades in an academic year. Core subjects are Math, Science, ELA, and Social Studies. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Figure 5: Morning Commute Time versus Sleep



Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional on age, sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday. (n = 1,407 students)

Table 6: Time Use Results

	Students (5-18)		Adults	
	Sleep	Leisure	Sleep	Leisure
ATUS				
AM Commute Time (Minutes)			-0.387***	-0.593***
			(0.048)	(0.051)
N			10,572	10,572
PSID-CDS				
AM Commute Time (Minutes)	-0.660***	-0.369***		
	(0.092)	(0.120)		
N	1,407	1,407		

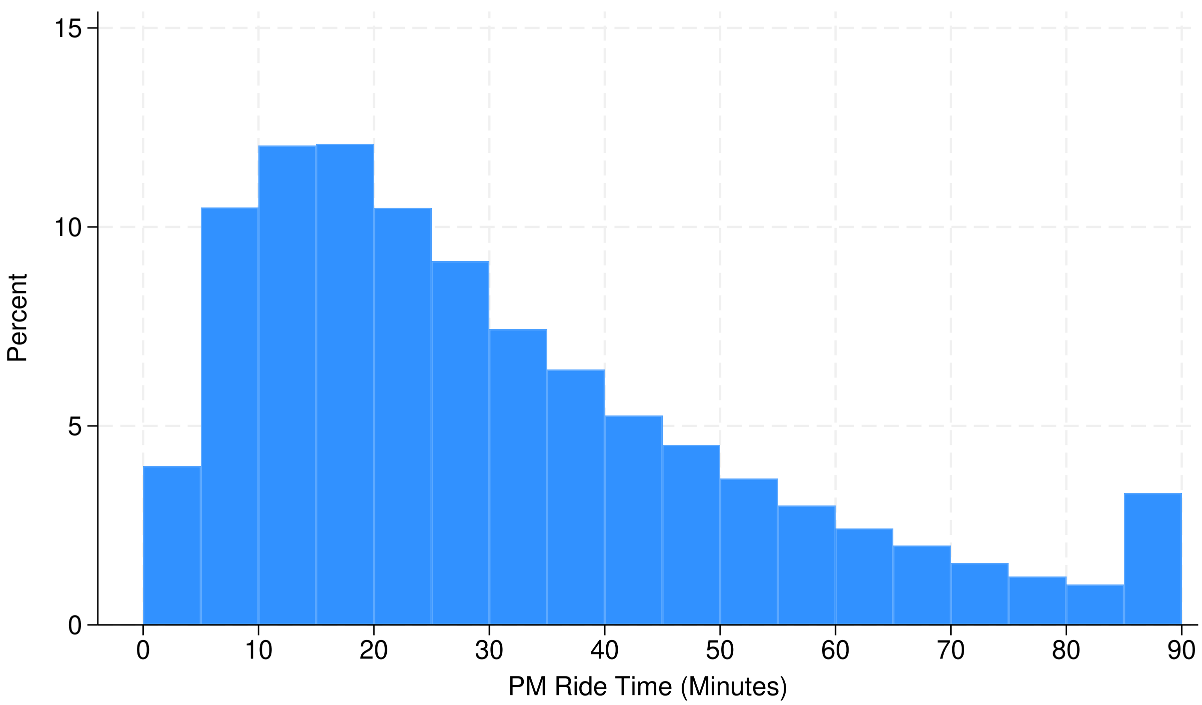
PSID-CDS data comes from the 2014 and 2019 surveys. American Time Use Survey data runs from 2003 through 2023. Regressions control for sex, age, race, family income, and year. Robust standard errors are listed in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Appendix A Figures and Tables

Figure A1: Sample Ridership Rates

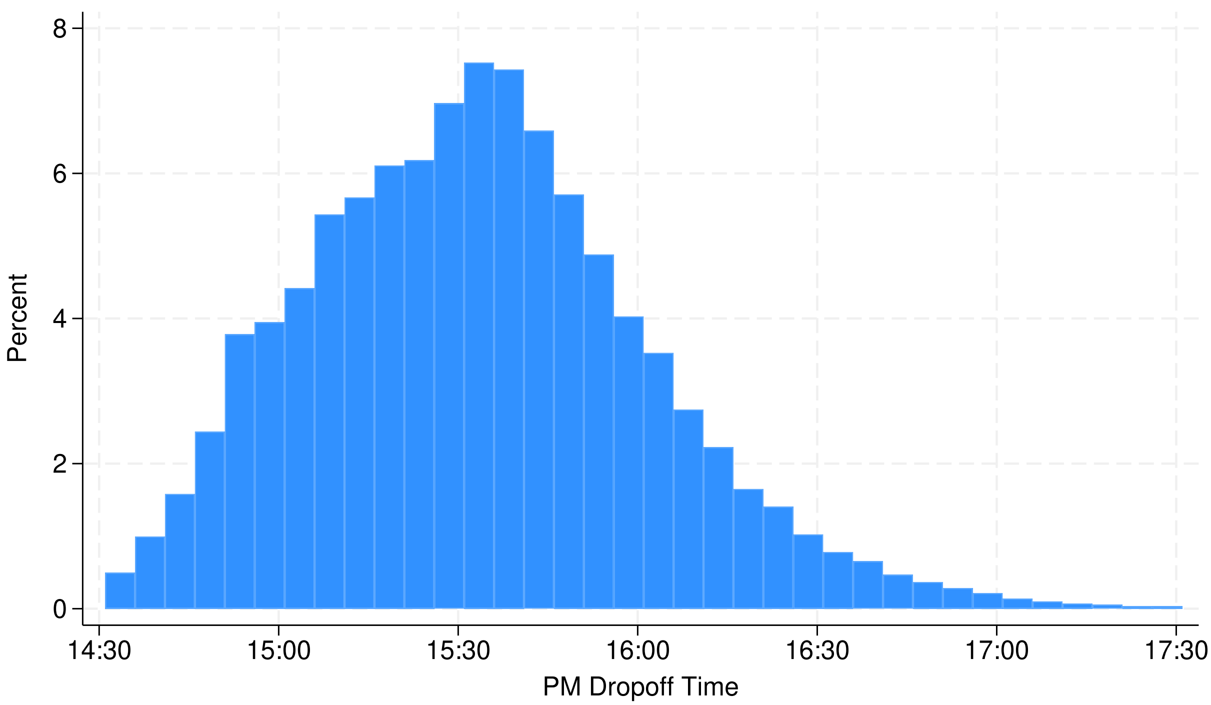
Ridership share is defined as the number of bus riders divided by the total number of students with positive attendance rates.

Figure A2: Characteristics of PM Bus Commutes



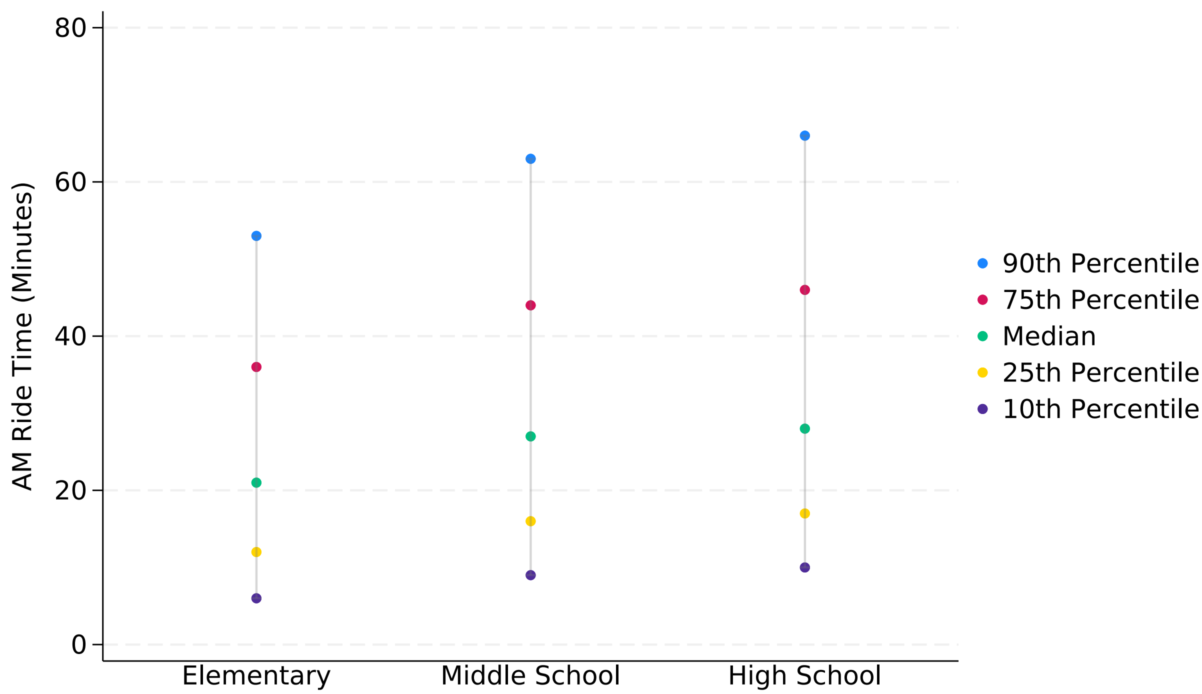
Percent calculated based on observations with non-missing attendance rates, race, and sex. Ride times longer than 90 minuets are binned at 90.

Figure A3: Characteristics of PM Bus Commutes



Percent calculated based on observations with non-missing attendance rates, race, and sex.

Figure A4: Distribution of AM Bus Ride Times by Grade Level



Elementary school is defined as grades K–5, Middle School is defined as grades 6–8, and High School is defined as grades 9–12. Percentiles are calculated based on all available years of data in the participating districts.

Table A1: Characteristics of Bus Riders by Ride Time, 2021–22 School Year

	0–30 Minutes		30–45 Minutes		45–60 Minutes		60+ Minutes	
	Mean	N	Mean	N	Mean	N	Mean	N
Race								
Asian	0.01	19,203	0.01	5,732	0.01	3,521	0.01	3,158
Black	0.17	19,203	0.14	5,732	0.11	3,521	0.10	3,158
Hispanic	0.31	19,203	0.29	5,732	0.30	3,521	0.30	3,158
White	0.45	19,203	0.50	5,732	0.53	3,521	0.53	3,158
Sex								
Female	0.47	19,203	0.47	5,732	0.47	3,521	0.47	3,158
Student Characteristics								
Gifted Status	0.07	19,203	0.09	5,732	0.08	3,521	0.09	3,158
Economically Disadvantaged	0.46	19,203	0.43	5,732	0.48	3,521	0.46	3,158
English Language Learner	0.15	19,203	0.13	5,732	0.14	3,521	0.13	3,158
Attendance								
Attendance Rate	90.48	19,225	90.36	5,739	89.87	3,524	89.48	3,162
Behavior								
Any Suspension	0.15	19,426	0.18	5,793	0.20	3,561	0.20	3,207
Any OSS	0.10	19,426	0.11	5,793	0.12	3,561	0.13	3,207
Any Bus-Related Suspension	0.02	19,426	0.02	5,793	0.03	3,561	0.03	3,207
Test Scores								
EOG Math Score (3–8)	-0.05	10,042	0.02	2,833	-0.03	1,769	-0.08	1,438
EOG Reading Score (3–8)	-0.11	10,274	-0.05	2,897	-0.12	1,809	-0.15	1,484
EOC Math 1 Score (HS)	0.06	1,666	0.06	621	0.09	387	0.09	451
EOC Math 3 Score (HS)	0.06	1,147	0.05	465	0.05	259	-0.01	268
EOC Biology Score (HS)	0.06	1,209	0.17	463	-0.03	311	0.13	295
EOC English 2 Score (HS)	-0.22	1,421	-0.13	515	-0.24	326	-0.12	352
ACT Composite Score	-0.20	1,064	-0.18	433	-0.16	254	-0.17	240
Grades (HS)								
All Courses	79.61	5,037	80.22	1,991	79.48	1,186	80.47	1,245
Core Courses	76.40	4,895	77.01	1,932	76.14	1,142	77.22	1,170
Core Math/Science Courses	75.39	4,666	75.88	1,826	75.00	1,079	76.36	1,117

Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Suspensions are categorized as bus-related if bus misbehavior is listed as a cause for the suspension. All test scores have been standardized at the test-by-grade-by-year level for the entire state.

Table A2: Covariate Balance Test

	AM Ride Time (Minutes)			
	1	2	3	4
Black	-5.861***	-1.031***	-4.725***	-0.480*
	(0.979)	(0.332)	(0.695)	(0.249)
Hispanic	-3.255***	-0.559*	-1.914***	0.081
	(0.689)	(0.288)	(0.650)	(0.232)
Female	-0.198	0.066	-0.092	0.033
	(0.126)	(0.088)	(0.106)	(0.080)
Economically Disadvantaged	0.630	0.729***	2.235***	1.026***
	(0.617)	(0.221)	(0.525)	(0.193)
N	236270	235058	236167	234955
Controls				
Home-to-School Distance			X	X
Fixed Effects				
Bus Route		X		X

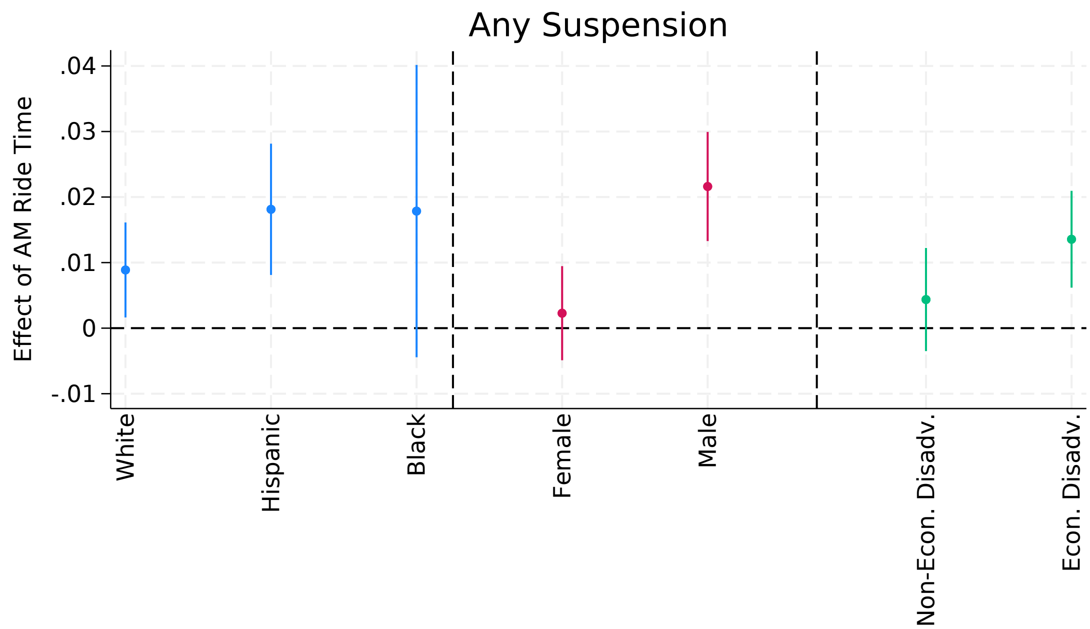
Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

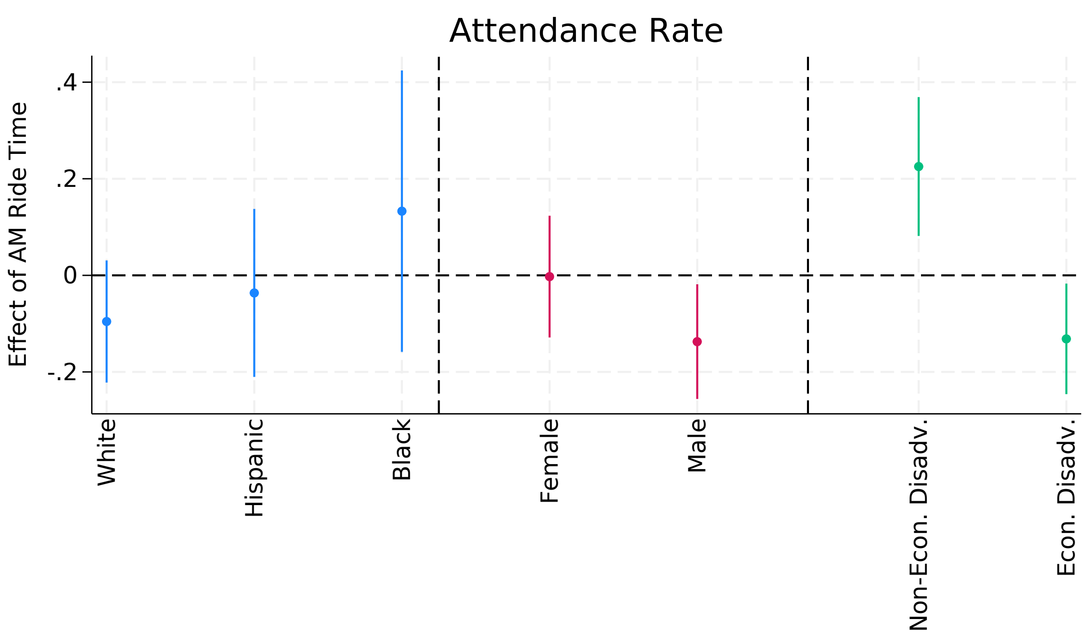
Table A3: ACT Results by Section

	English	Math	Reading	Science
AM Ride Time (Hours)	-0.041	-0.027	-0.062*	-0.052**
	(0.026)	(0.024)	(0.034)	(0.025)
PM Ride Time (Hours)	0.013	-0.014	-0.011	0.015
	(0.034)	(0.038)	(0.028)	(0.037)
Outcome Mean	-0.177	-0.233	-0.169	-0.157
N	11095	11091	11087	11082
Controls				
Home-to-School Walking Distance	X	X	X	X
Fixed Effects				
Bus Route	X	X	X	X
Distance Ring				

ACT sections are taken in a fixed order: English, Math, 10-minute break, Reading, and Science. Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

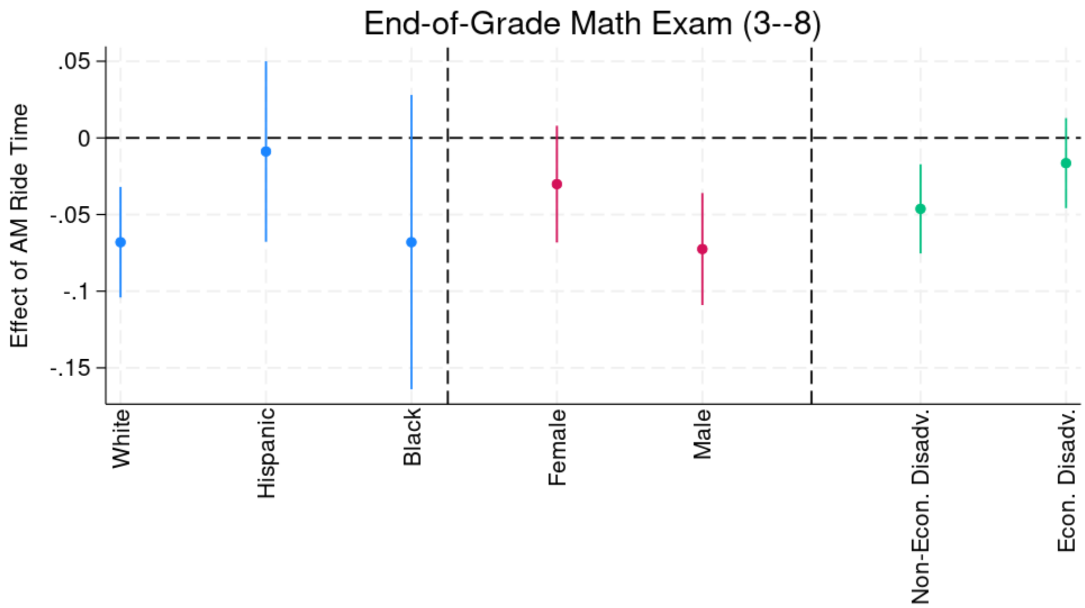
Figure A5: Effect Heterogeneity—Behavior and Attendance

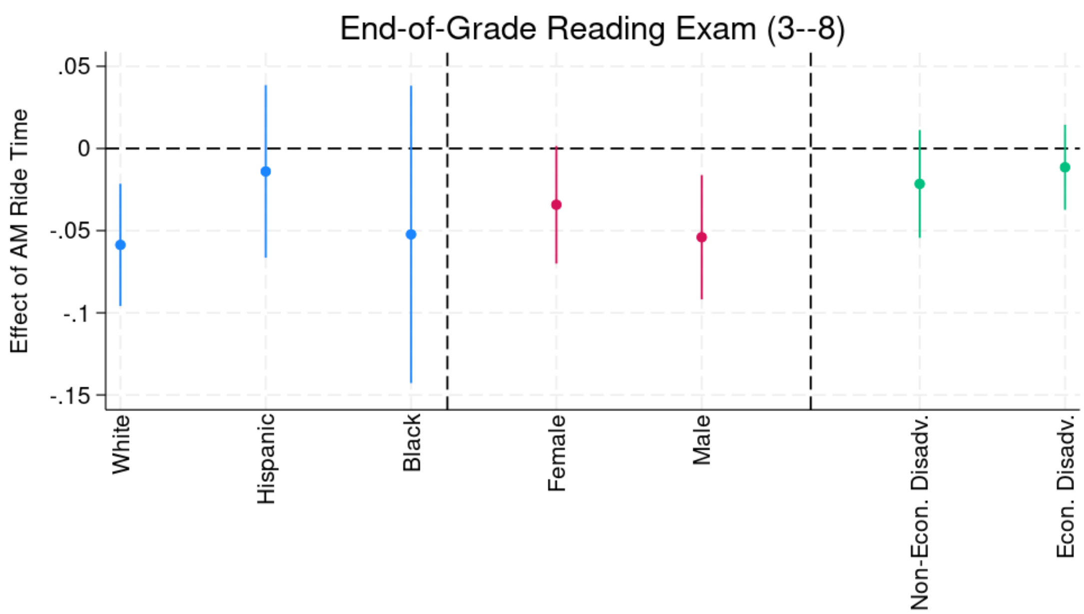




All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level and bars plot the 95 percent confidence interval.

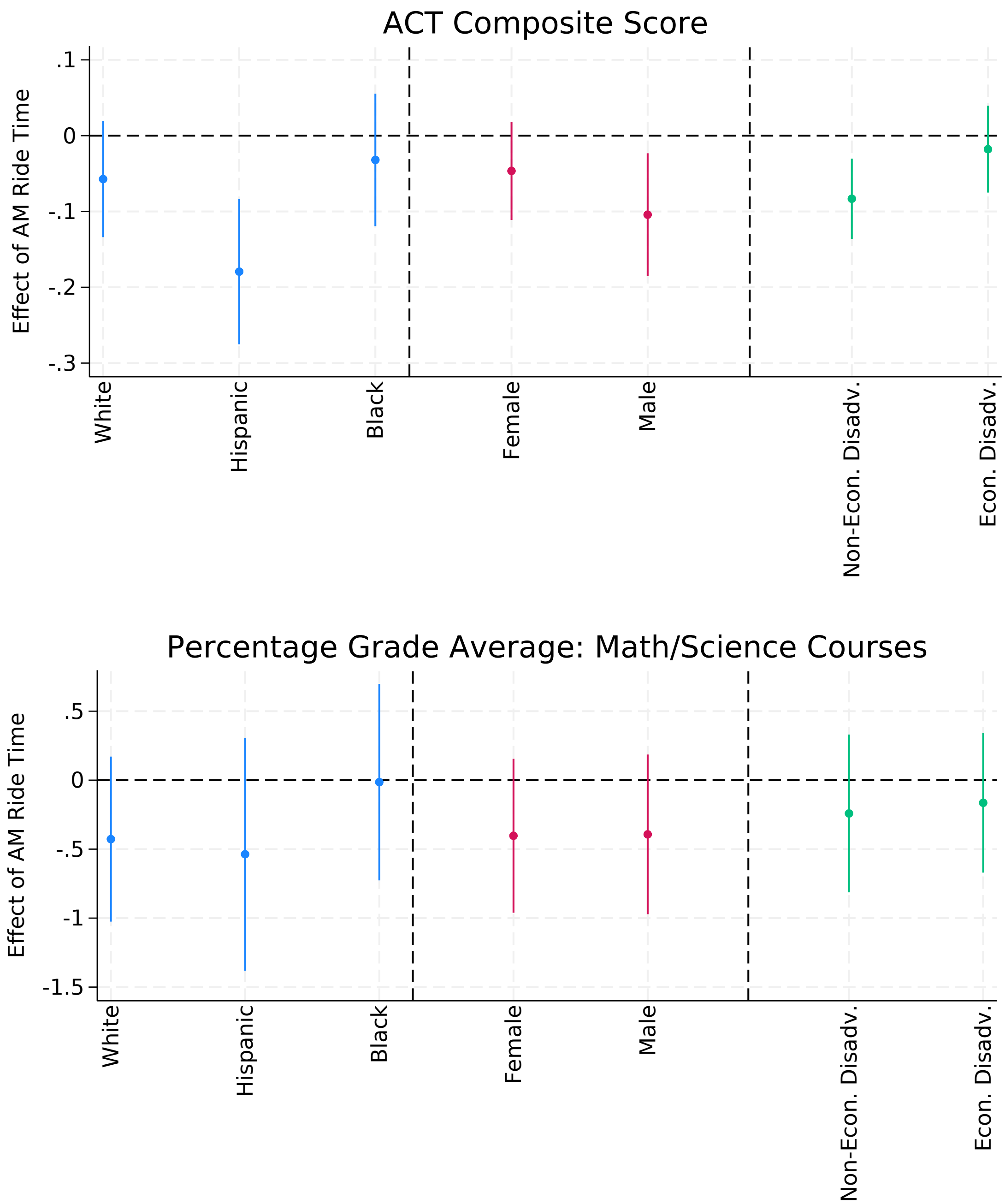
Figure A6: Testing Effect Heterogeneity—End-of-Grade Exams





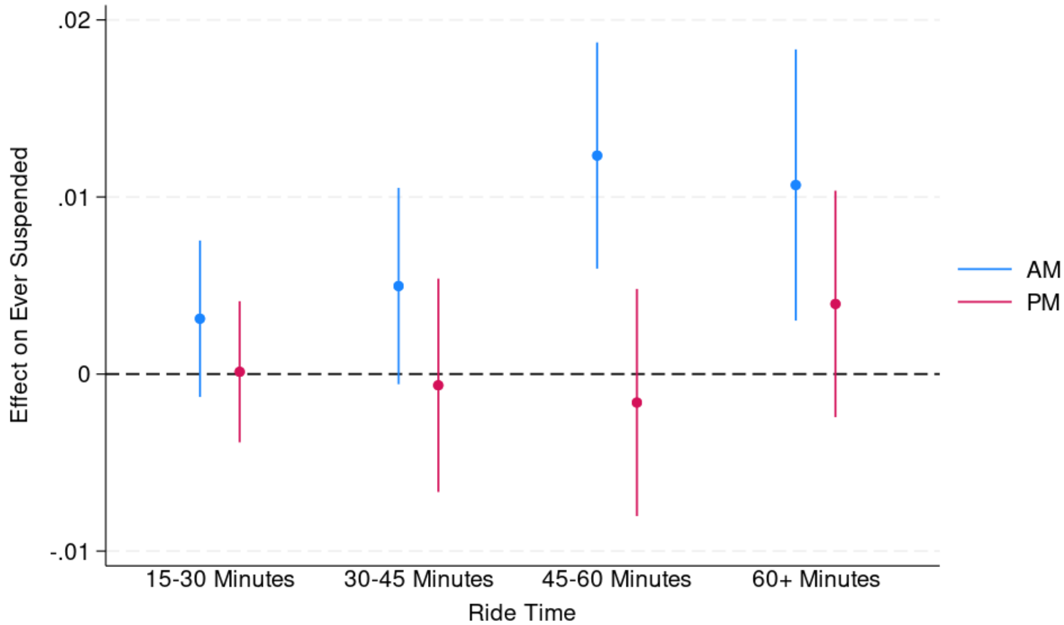
Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level and bars plot the 95 percent confidence interval.

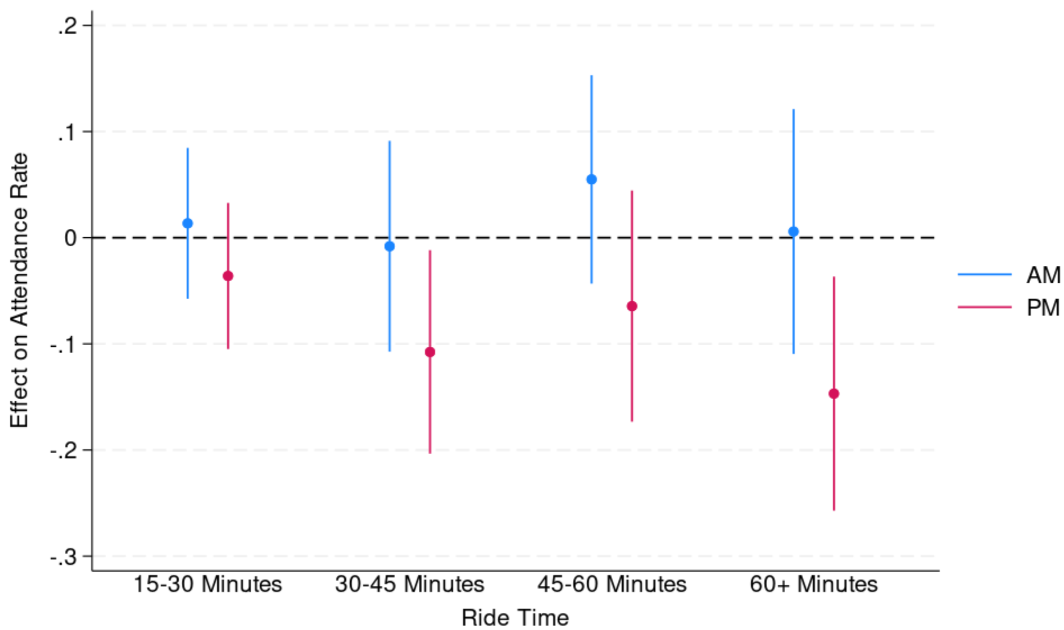
Figure A7: Testing Effect Heterogeneity—ACT and Grades



Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Grades are calculated as the average of all GPA-eligible final grades in an academic year. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level and bars plot the 95 percent confidence interval.

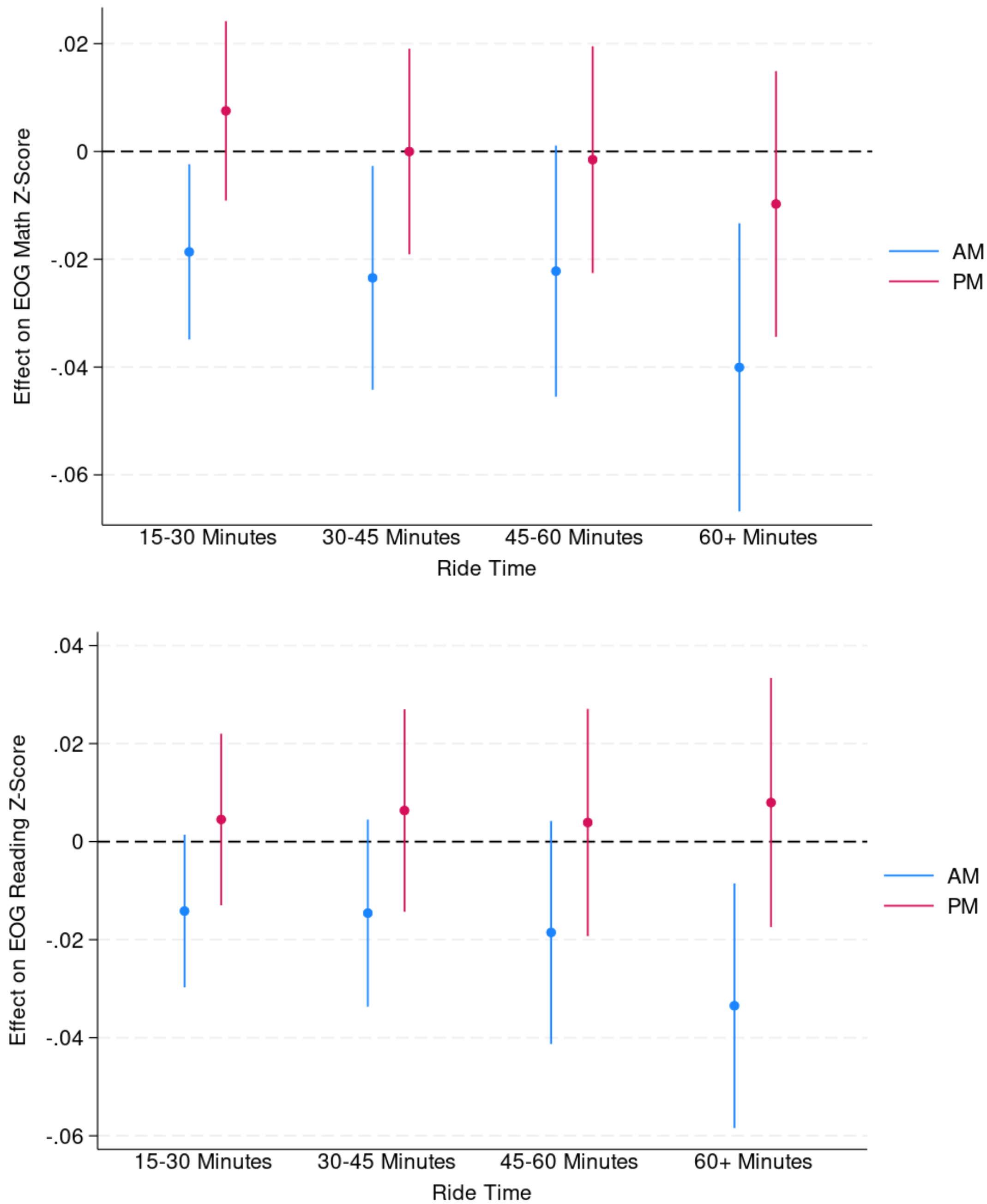
Figure A8: Effects By Ride Time Bin





All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level and bars plot the 95 percent confidence interval.

Figure A9: Effects By Ride Time Bin



Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level and bars plot the 95 percent confidence interval.

Table A4: Behavior Results—Lagged Outcome Control

	1	2	3	4
	Any Suspension			
AM Ride Time (Hours)	0.007***	0.006**	0.009***	0.008***
	(0.002)	(0.003)	(0.002)	(0.003)
PM Ride Time (Hours)	-0.002	-0.002	-0.000	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Outcome Mean	0.152	0.152	0.152	0.152
N	291588	291378	290427	290234
	Bus Suspension			
AM Ride Time (Hours)	0.005***	0.002	0.006***	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.010***	0.007***	0.011***	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)
Outcome Mean	0.027	0.027	0.027	0.027
N	291588	291378	290427	290234
	Non-Bus Suspension			
AM Ride Time (Hours)	0.005*	0.006**	0.006**	0.007***
	(0.002)	(0.003)	(0.002)	(0.003)
PM Ride Time (Hours)	-0.006**	-0.006**	-0.005**	-0.004*
	(0.003)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.137	0.137	0.137	0.137
N	291588	291378	290427	290234
Controls				
Home-to-School Walking Distance		X		X
Lagged Outcome	X	X	X	X
Fixed Effects				
Bus Route			X	X

I define a student as having a bus suspension within a given academic year if they ever receive out-of-school or in-school suspension during that year with the cause of the suspension listed as bus misbehavior. All other suspensions are classified as non-bus suspensions. All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table A5: Attendance Results—Lagged Outcome Control

	1	2	3	4
	Attendance Rate			
AM Ride Time (Hours)	-0.080**	-0.026	0.013	0.018
	(0.038)	(0.040)	(0.033)	(0.050)
PM Ride Time (Hours)	-0.102***	-0.057**	-0.094***	-0.098**
	(0.030)	(0.029)	(0.032)	(0.043)
Outcome Mean	94.924	94.924	94.929	94.953
N	291588	291378	290427	295194
	Chronic Absenteeism			
AM Ride Time (Hours)	0.004*	0.001	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.005***	0.003	0.006***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.114	0.114	0.114	0.114
N	291588	291378	290427	290234
Controls				
Home-to-School Walking Distance		X		X
Lagged Outcome	X	X	X	X
Fixed Effects				
Bus Route			X	X

Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A6: Testing Results—Lagged Outcome Control

	1	2	3	4
	End-of-Grade Math (3–8)			
AM Ride Time (Hours)	-0.013**	-0.012*	-0.013**	-0.014**
	(0.006)	(0.006)	(0.007)	(0.007)
PM Ride Time (Hours)	0.003	0.004	0.005	0.004
	(0.007)	(0.008)	(0.008)	(0.008)
Outcome Mean	0.138	0.138	0.140	0.139
N	84657	84629	84391	84363
	End-of-Grade Reading (3–8)			
AM Ride Time (Hours)	-0.006	-0.008	-0.007	-0.005
	(0.007)	(0.007)	(0.006)	(0.007)
PM Ride Time (Hours)	0.003	0.001	0.004	0.006
	(0.006)	(0.006)	(0.007)	(0.007)
Outcome Mean	0.147	0.147	0.148	0.148
N	81225	81193	80954	80922
Controls				
Home-to-School Walking Distance		X		X
Lagged Outcome	X	X	X	X
Fixed Effects				
Bus Route			X	X

Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A7: Grade Results—Lagged Outcome Control

	1	2	3	4
	Core Subject Grades			
AM Ride Time (Hours)	-0.139	-0.103	0.025	0.027
	(0.130)	(0.147)	(0.109)	(0.118)
PM Ride Time (Hours)	-0.338**	-0.309*	-0.047	-0.049
	(0.156)	(0.164)	(0.123)	(0.129)
Outcome Mean	80.080	80.077	80.050	80.047
N	59885	59809	59245	59180
	Math and Science Grades			
AM Ride Time (Hours)	-0.119	-0.070	-0.130	-0.133
	(0.139)	(0.172)	(0.136)	(0.163)
PM Ride Time (Hours)	-0.418**	-0.383**	-0.123	-0.145
	(0.175)	(0.187)	(0.153)	(0.178)
Outcome Mean	79.194	79.192	79.154	79.152
N	56528	56460	55896	55840
Controls				
Home-to-School Walking Distance		X		X
Lagged Outcome	X	X	X	X
Fixed Effects				
Bus Route			X	X

Grades are calculated as the average of all GPA-eligible final grades in an academic year. Core subjects are Math, Science, ELA, and Social Studies. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A8: Behavior Results—Robustness

	1	2	3	4	5
			Any Suspension		
AM Ride Time (Hours)	0.006*	0.010***	0.010**	0.008	0.007*
	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)
PM Ride Time (Hours)	-0.004	-0.001	-0.004	-0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
Outcome Mean	0.151	0.151	0.151	0.144	0.152
N	296289	295143	289555	145791	257888
			Bus Suspension		
AM Ride Time (Hours)	0.003*	0.004**	0.004**	0.010**	0.002
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)
PM Ride Time (Hours)	0.008***	0.008***	0.009***	0.003	0.012***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Outcome Mean	0.027	0.027	0.027	0.029	0.028
N	296289	295143	289555	145791	257888
			Non-Bus Suspension		
AM Ride Time (Hours)	0.005	0.007**	0.007**	0.002	0.006
	(0.003)	(0.003)	(0.004)	(0.007)	(0.004)
PM Ride Time (Hours)	-0.008***	-0.005*	-0.008**	-0.002	-0.005
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
Outcome Mean	0.137	0.137	0.137	0.129	0.137
N	296289	295143	289555	145791	257888
Fixed Effects					
Bus Route		X			
Distance Ring	X	X			
Bus Route X Distance Ring			X		
Census Block				X	
Student					X

I define a student as having a bus suspension within a given academic year if they ever receive out-of-school or in-school suspension during that year with the cause of the suspension listed as bus misbehavior. All other suspensions are classified as non-bus suspensions. All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. The student fixed effect specification includes a control for home-to-school distance. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A9: Attendance Results—Robustness

	1	2	3	4	5
			Attendance Rate		
AM Ride Time (Hours)	-0.087*	0.003	0.038	-0.083	0.046
	(0.049)	(0.051)	(0.063)	(0.068)	(0.061)
PM Ride Time (Hours)	-0.092**	-0.095**	-0.069	-0.063	-0.162***
	(0.046)	(0.045)	(0.056)	(0.058)	(0.052)
Outcome Mean	94.948	94.953	94.967	95.837	95.218
N	296289	295143	289555	145791	257888
			Chronic Absenteeism		
AM Ride Time (Hours)	0.005*	-0.000	0.000	0.004	-0.002
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
PM Ride Time (Hours)	0.003	0.004*	0.004	-0.002	0.005*
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)
Outcome Mean	0.114	0.114	0.113	0.071	0.100
	296289	295143	289555	145791	257888
Fixed Effects					
Bus Route		X			
Distance Ring	X	X			
Bus Route X Distance Ring			X		
Census Block				X	
Student					X

Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Suspensions are categorized as bus-related if bus misbehavior is listed as a cause for the suspension. All test scores have been standardized at the test-by-grade-by-year level for the entire state. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. The student fixed effect specification includes a control for home-to-school distance. Standard errors are clustered at the school level. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table A10: Testing Sample—Robustness

	1	2	3	4	5
			End-of-Grade Math (3–8)		
AM Ride Time (Hours)	-0.026**	-0.027**	-0.015	-0.026	-0.006
	(0.011)	(0.012)	(0.014)	(0.022)	(0.010)
PM Ride Time (Hours)	-0.004	-0.001	0.003	-0.022	-0.017*
	(0.010)	(0.010)	(0.012)	(0.018)	(0.010)
Outcome Mean	0.092	0.094	0.093	0.173	0.100
N	111400	111081	108702	36835	80006
			End-of-Grade Reading (3–8)		
AM Ride Time (Hours)	-0.018*	-0.017	-0.005	0.001	-0.003
	(0.010)	(0.011)	(0.013)	(0.021)	(0.010)
PM Ride Time (Hours)	-0.000	0.002	0.006	-0.016	-0.009
	(0.011)	(0.011)	(0.013)	(0.022)	(0.007)
Outcome Mean	0.096	0.098	0.097	0.171	0.105
N	107584	107280	104889	34147	76791
Fixed Effects					
Bus Route		X			
Distance Ring	X	X			
Bus Route X Distance Ring			X		
Census Block				X	
Student					X

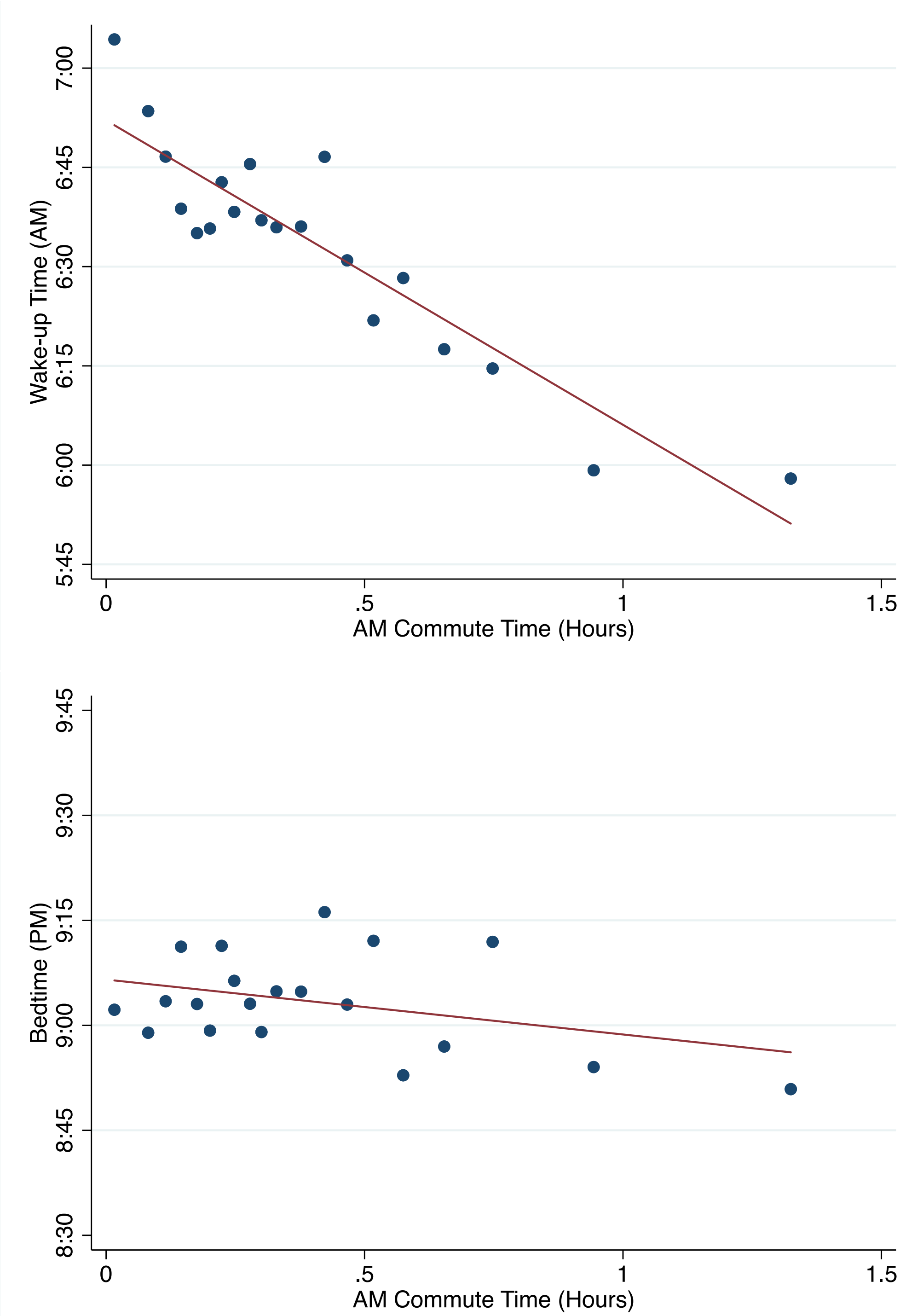
Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. The student fixed effect specification includes a control for home-to-school distance. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A11: Grade Results—Robustness

	1	2	3	4	5
			Core Subject Grades		
AM Ride Time (Hours)	-0.183	-0.081	-0.087	-0.207	0.180
	(0.202)	(0.200)	(0.247)	(0.242)	(0.202)
PM Ride Time (Hours)	-0.242	-0.267	-0.375	-0.291	-0.287
	(0.212)	(0.208)	(0.265)	(0.333)	(0.245)
Outcome Mean	80.192	80.162	80.129	81.347	80.690
N	87059	86274	84205	41167	63002
			Math and Science Grades		
AM Ride Time (Hours)	-0.110	-0.087	-0.064	-0.153	0.205
	(0.186)	(0.195)	(0.235)	(0.208)	(0.174)
PM Ride Time (Hours)	-0.352	-0.382	-0.478	-0.344	-0.238
	(0.241)	(0.241)	(0.291)	(0.389)	(0.204)
Outcome Mean	79.326	79.291	79.258	80.493	79.867
N	83623	82876	80871	39789	59719
Fixed Effects					
Bus Route		X			
Distance Ring	X	X			
Bus Route X Distance Ring			X		
Census Block				X	
Student					X

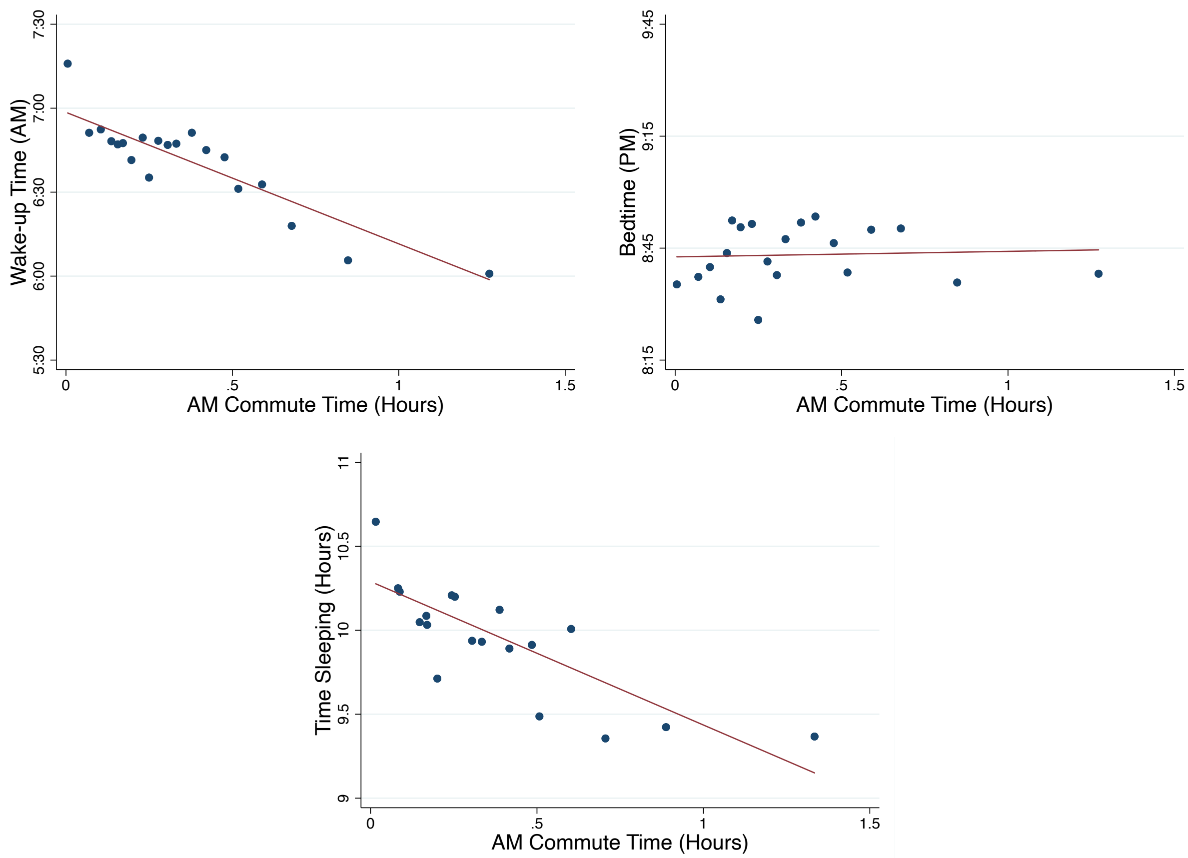
Grades are calculated as the average of all GPA-eligible final grades in an academic year. Core subjects are Math, Science, ELA, and Social Studies. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year. The student fixed effect specification includes a control for home-to-school distance. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Figure A10: Morning Commute Time versus Sleep



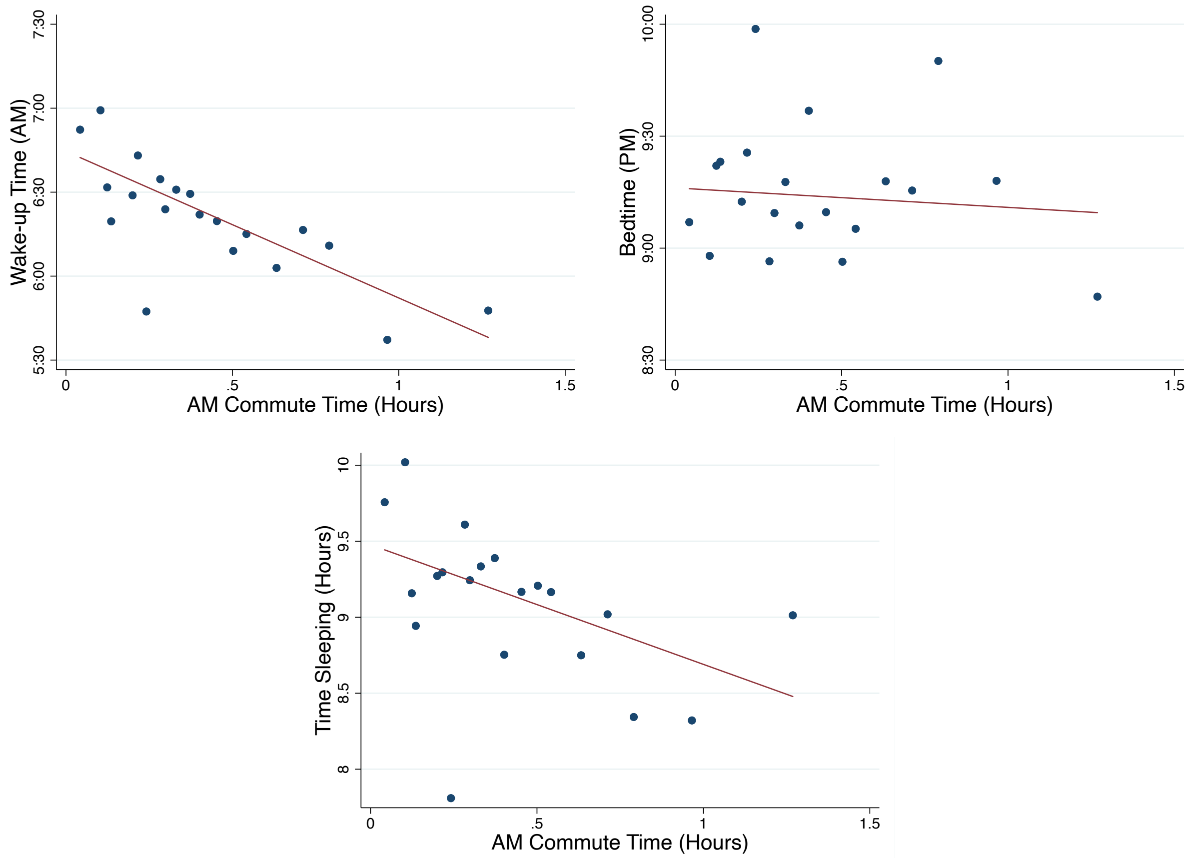
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional on age, sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday. (n = 1,407 students)

Figure A11: AM Commute Time versus Sleep – Elem. Students (6–10 years old; n=784)



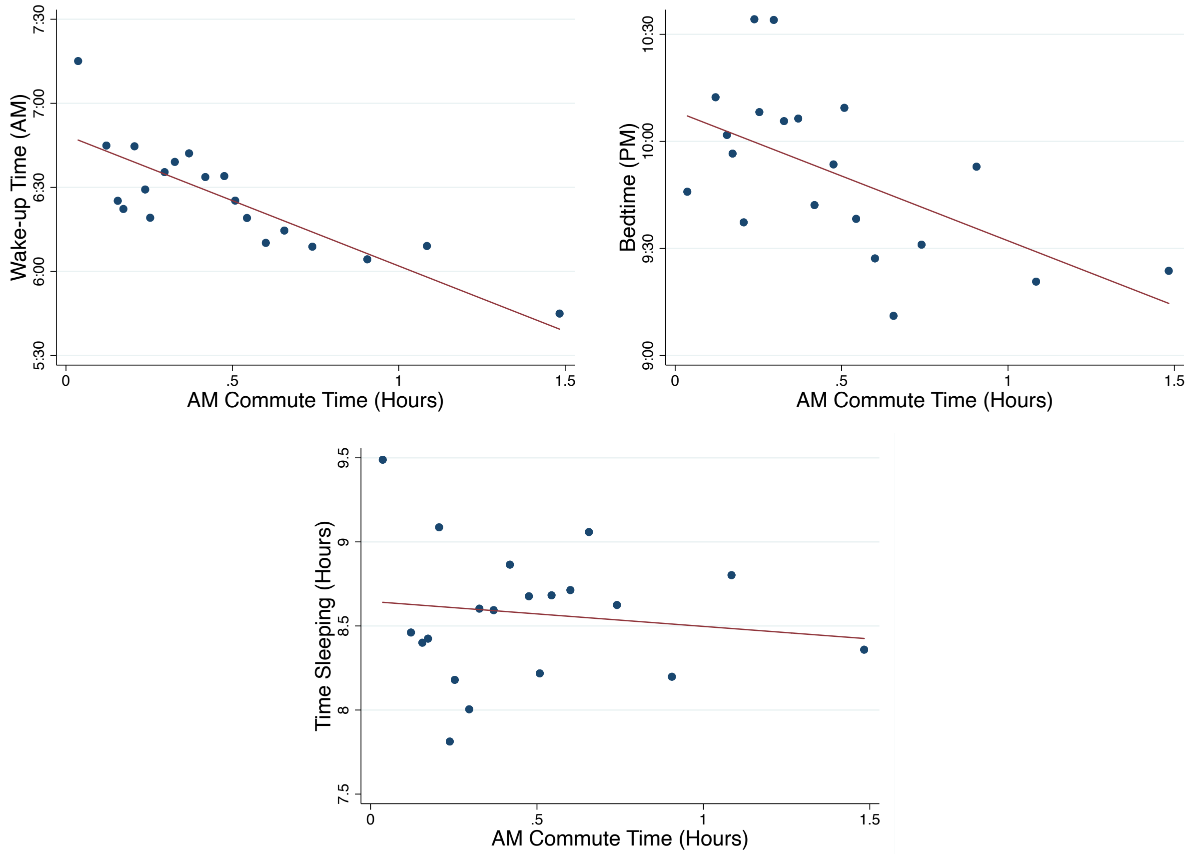
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A12: Morning Commute Time versus Sleep – MS Students (11–13 years old; n=318)



Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A13: Morning Commute Time versus Sleep – HS Students (14–17 years old; n=305)

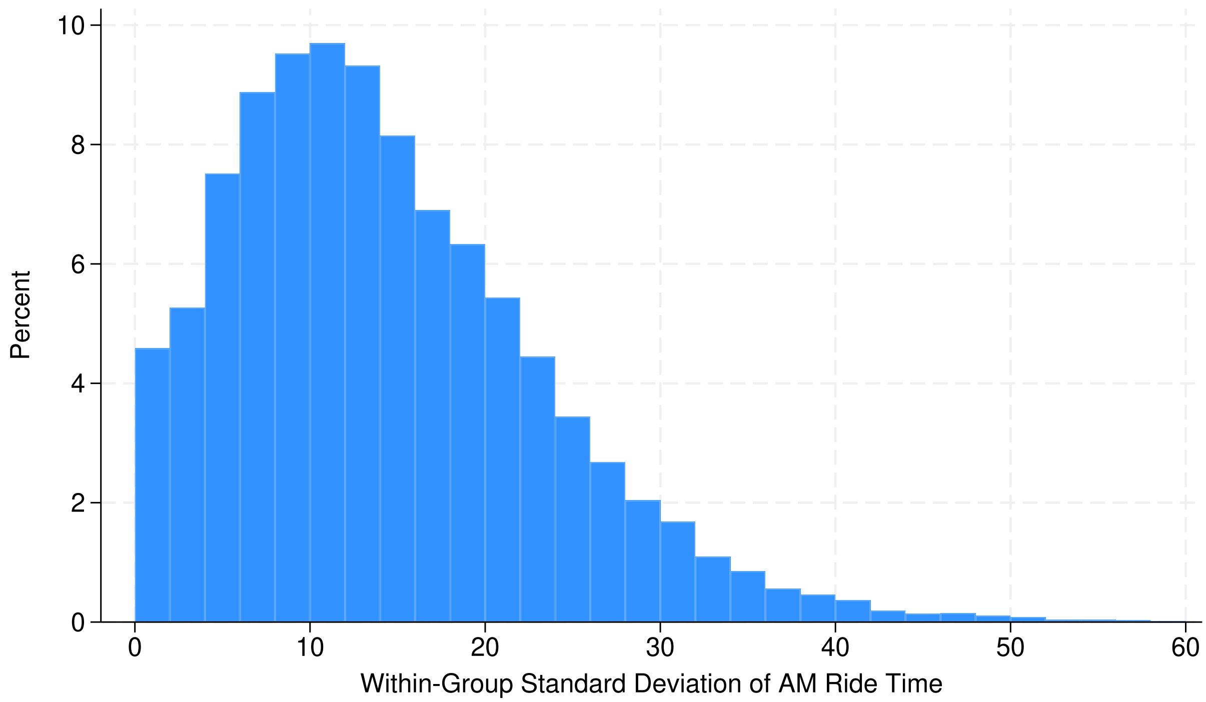


Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Appendix B Variation within Comparison Groups

B.1 Bus Route Fixed Effects

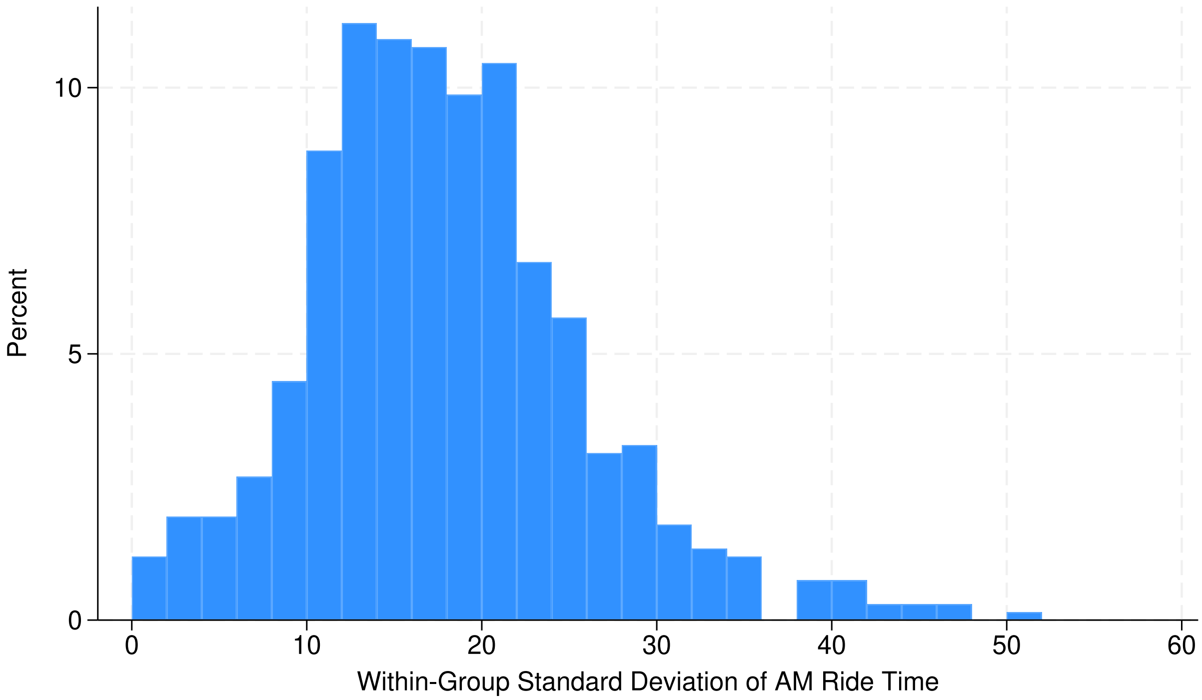
Figure B1: Variation within Bus Route



For each bus route, I calculate the standard deviations of ride times for all riders with non-missing race, sex, disability status, gifted status, and English language learner status.

B.2 Distance Ring Fixed Effects

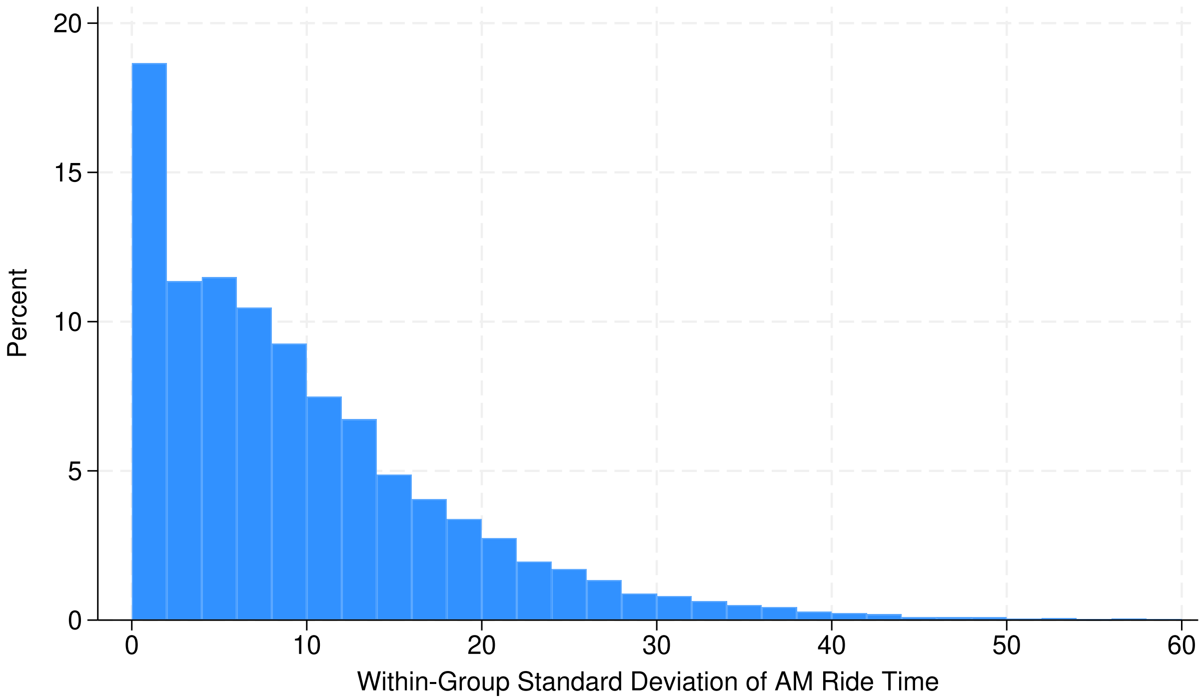
Figure B2: Variation within Distance Ring



For each distance ring at each school, I calculate the standard deviations of ride times for all riders with non-missing race, sex, disability status, gifted status, and English language learner status.

B.3 Bus Route × Distance Ring Fixed Effects

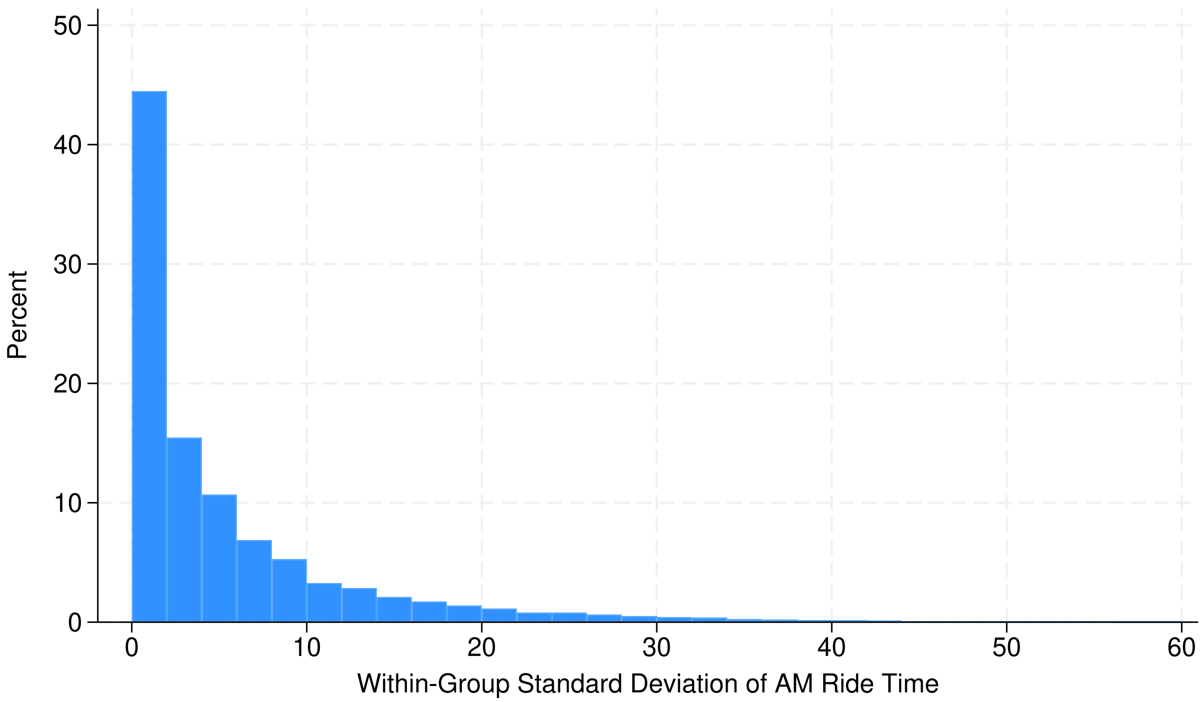
Figure B3: Variation within Distance Ring × Bus Route



For each distance ring by bus route group at each school, I calculate the standard deviations of ride times for all riders with non-missing race, sex, disability status, gifted status, and English language learner status.

B.4 Census Blocks

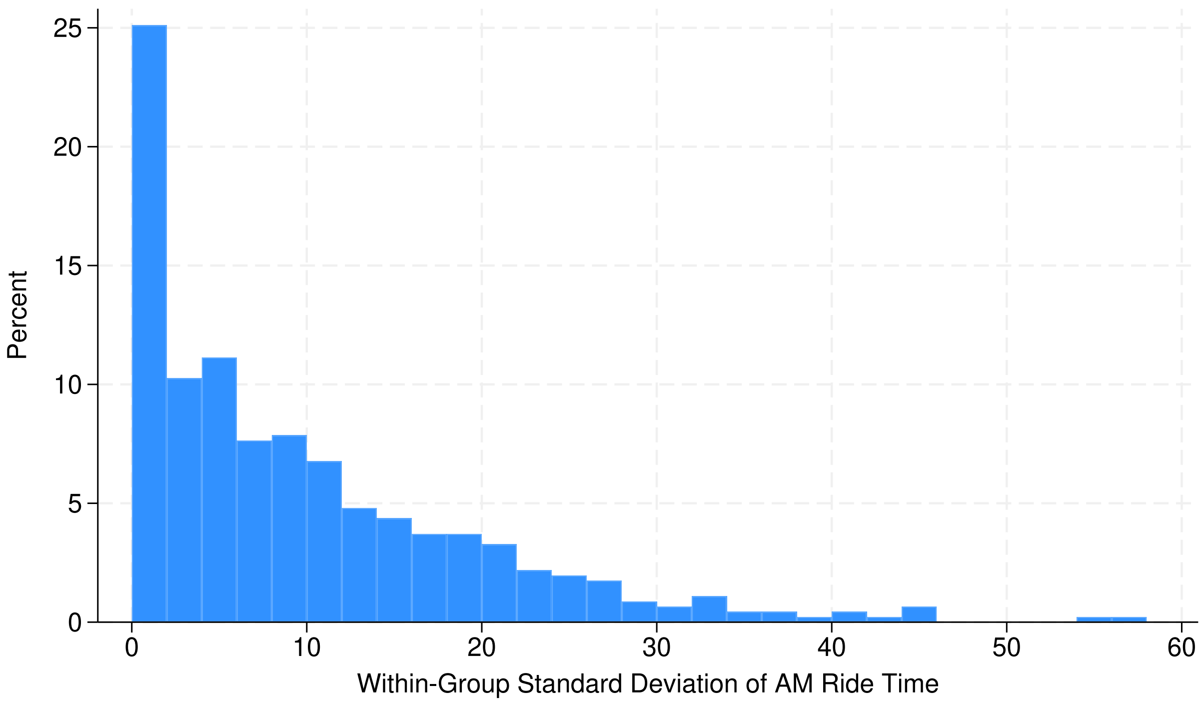
Figure B4: Variation within Census Block



For each Census block, I calculate the standard deviations of ride times for all riders with non-missing race, sex, disability status, gifted status, and English language learner status.

B.5 Students

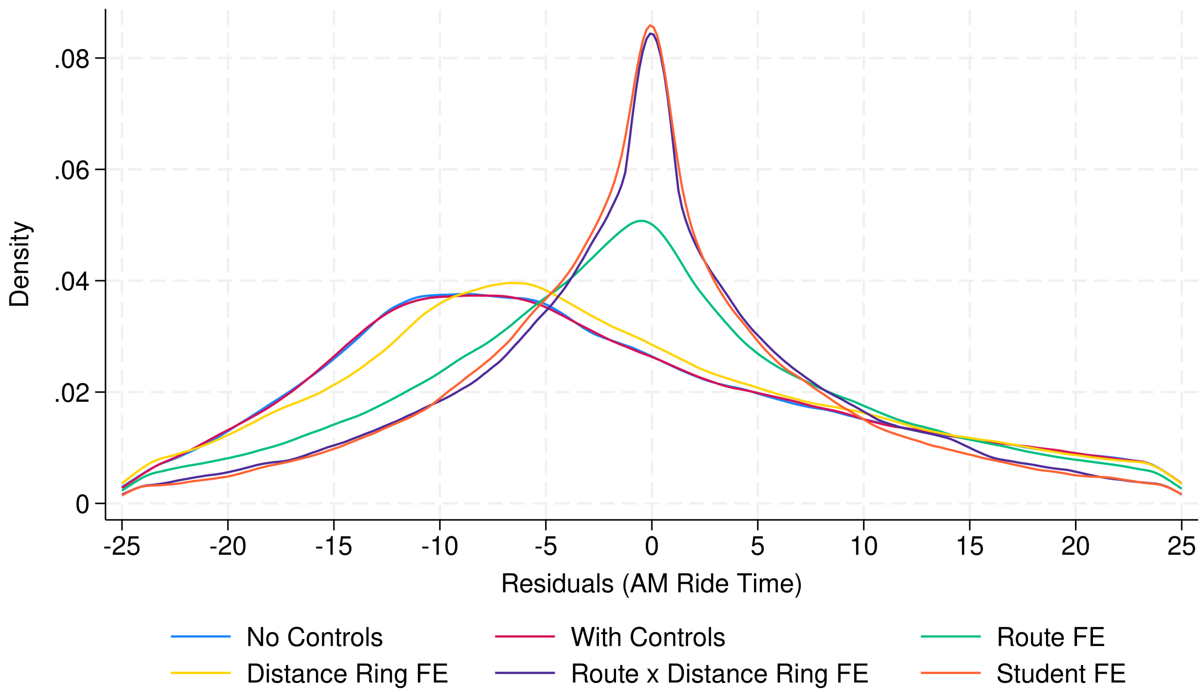
Figure B5: Variation within Student



For each student, I calculate the standard deviations of ride times across all available years.

B.6 Residual Variation

Figure B6: Residuals–AM Ride Time



Residuals are calculated as the difference between actual and predicted AM ride time based on regressing AM ride time on home-to-school distance using the attendance panel. Controls include economically disadvantaged status, disability status, gifted status, ELL status, race, gender, and grade. Home-to-school distance is not included in specifications that include distance ring fixed effects.

Appendix C Simulation of Bus Route Optimization

In this appendix, I present a simulation of the bus route optimization problem for an average school in my sample, which has 343 students and 10 school buses.

C.1 Simulation Parameters

First, I simulate a road grid centered around a school building. Within one mile of the school, roads are drawn in a 0.25 mile-by-0.25 mile grid. Between one and five miles from the school, roads are drawn in a 0.5 mile-by-0.5 mile grid. Outside of five miles from the school, roads are in a 1 mile-by-1 mile grid. Next, I randomly assign students to home locations on the road grid to match the distribution of home-to-school distance from Figure 3.

I allow school buses to traverse their routes with speed limits of 25 miles per hour (within one mile of the school), 35 miles per hour (one to three miles from the school), 45 miles per hour (three to five miles from the school), and 55 miles per hour (more than five miles from the school). I give each bus a capacity of 50 students.

Each stop takes 30 seconds if two or fewer students are picked up and one minute if more than two students are picked up. Students are allowed to walk up to 0.25 miles to be picked up at a community bus stop.

C.2 Optimization Approach

The school bus routing problem is an example of a vehicle routing problem (VRP). (Dantzig and Ramser 1959) The objective is to find the optimal routes for a fleet of vehicles to cover a set of pick-up or drop-off locations. Here, I attempt to optimize based on three potential objectives that school transportation directors consider when drawing bus routes: minimizing average ride time, minimizing maximum ride time, and minimizing miles driven.

I optimize in three stages. I use k-means clustering to separate riders into routes, obeying the capacity constraint of 50 for each bus. (Pedregosa et al. 2011) Next, I use a nearest-neighbor approach to draw an initial route for each bus, causing the buses to travel to the nearest available pick-up point after each stop. Finally, I use a 2-opt algorithm which allows for a local search around each pick-up point to check for possible route improvements. (Croes 1958)

C.3 Simulated Routes

This approach does not approach the cutting edge of the VRP; however, it (1) shows that it is possible to reduce average ride time, maximum ride time, or miles driven substantially through prioritization of each factor in routing design; and (2) generates routes and summary statistics that approximate the actual ride experiences in my sample.

Figures C1-C3 plot the simulated routes for each of the three optimization priorities. Table C1 gives summary statistics resulting from each routing choice. Notably, school districts may prefer to prioritize miles driven in their optimization because this leads to a reduction in fuel costs and benefits them in the state funding formula, which prioritizes efficiency. This simulation shows that the miles-driven approach leads to a 27 percent increase in average ride time relative to prioritizing average ride time. However, prioritizing average ride time forces buses to travel an extra 61 miles each morning compared to the cost-minimizing approach, an increase of 14.3 percent.

Table C1: Simulated Bus Routes – Summary Statistics

Routing Prioritization	Average Ride Time	Maximum Ride Time	Total Miles
Minimize Average Ride Time	30.7	86.4	489
Minimize Maximum Ride Time	38.2	76.9	434
Minimize Miles Driven	38.9	85.5	428

C.4 Simulation of Policy Option: Adding a School Bus

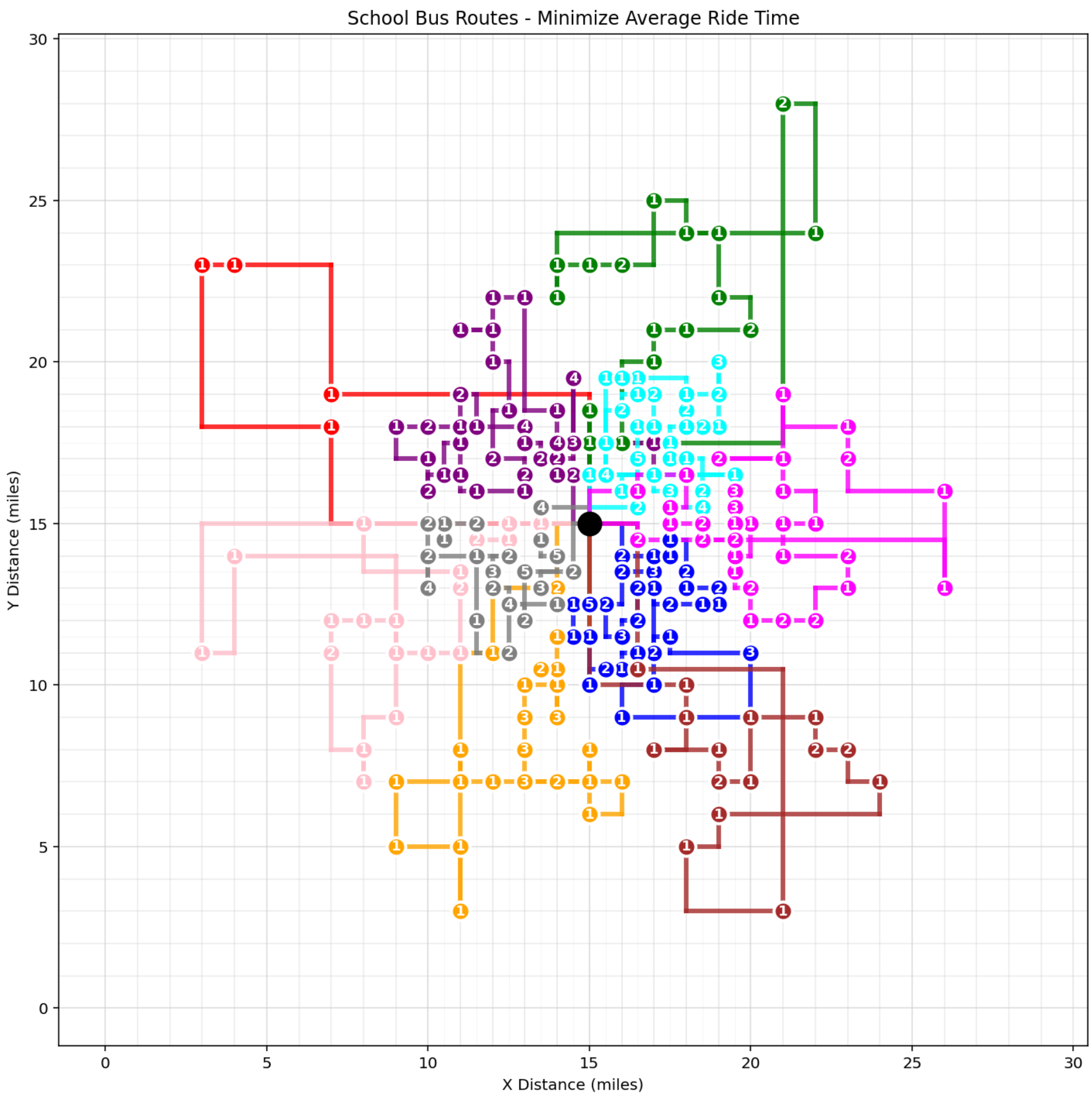
In this section, I simulate the impact on average ride time from adding one bus to the average school's fleet–taking the fleet from 10 to 11 buses with no change in the number of students. This exercise informs the policy discussion in Section 5.6.

Table C2: Change in Rides from 10 to 11 Buses

		Effect of Additional Bus	
Routing Prioritization	Average Ride Time	Minutes	Percent
Minimize Average Ride Time	29.4	-1.3	-4.2%
Minimize Maximum Ride Time	33.3	-4.9	-12.8%
Minimize Miles Driven	34.5	-4.4	-11.3%

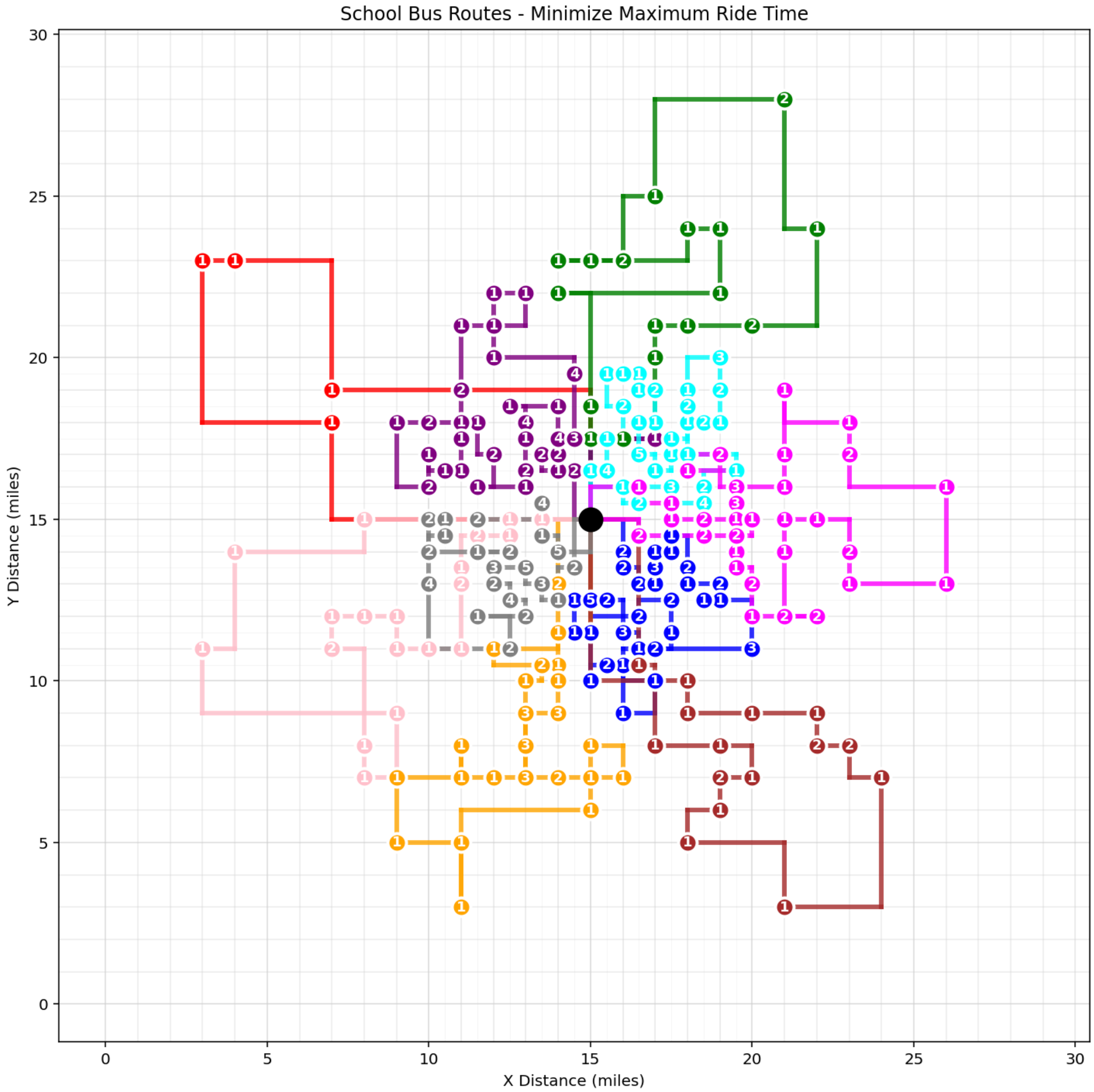
Table C2 shows that, depending on the prioritization method, adding a school bus to the fleet allows for a 4.2–11.3 percent reduction in a school's average ride time. If a school was trying to minimize cost with 10 buses and switched to minimizing average ride time with 11 buses, it could reduce the average ride time by 24.4 percent in this simulation.

Figure C1: Map of Simulated Bus Routes – Minimize Average Ride Time



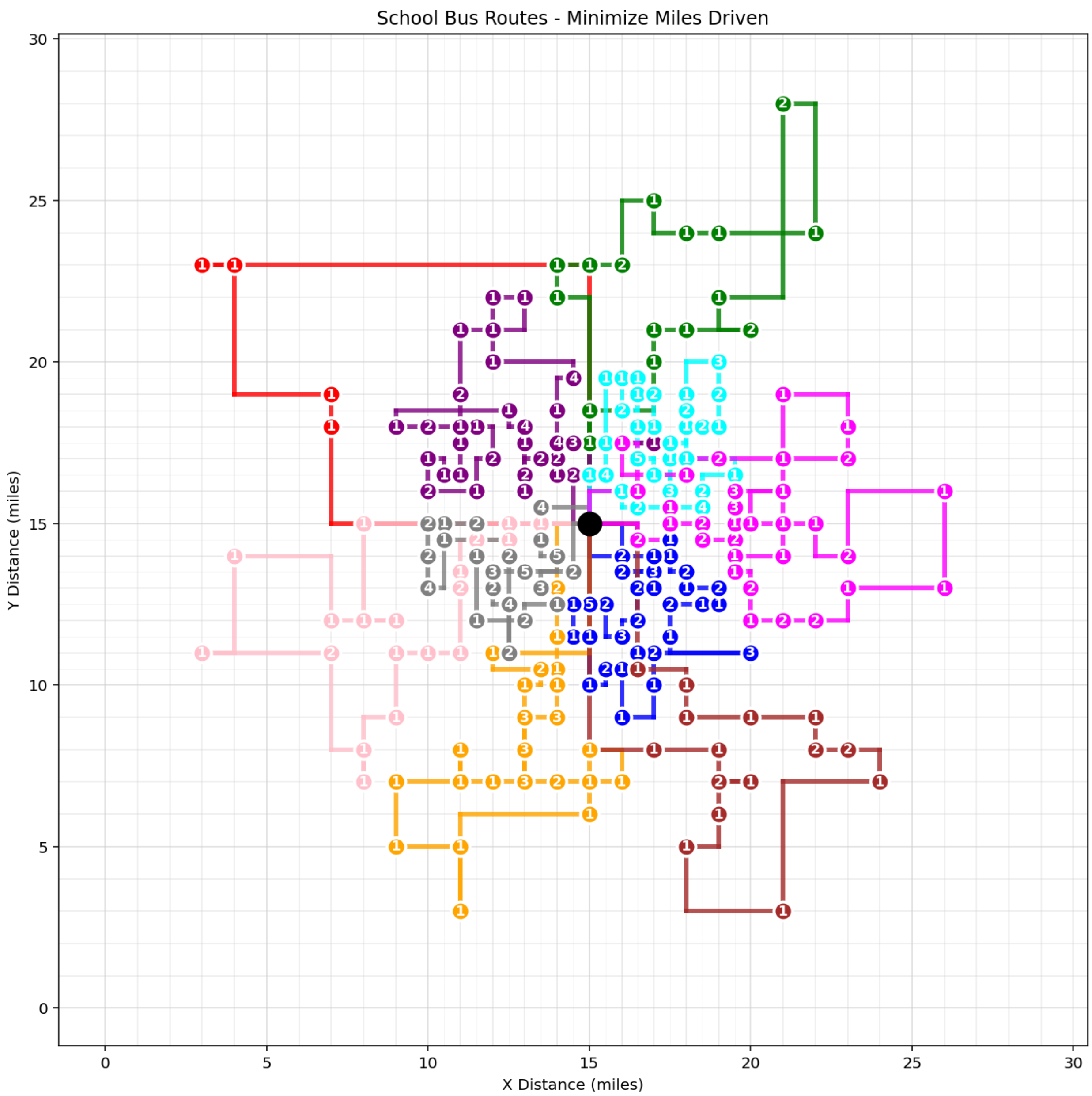
The number in each pick-up node represents the number of students picked up at that bus stop. The black dot in the center of the grid is the location of the school building.

Figure C2: Map of Simulated Bus Routes – Minimize Maximum Ride Time



The number in each pick-up node represents the number of students picked up at that bus stop. The black dot in the center of the grid is the location of the school building.

Figure C3: Map of Simulated Bus Routes – Minimize Miles Driven



The number in each pick-up node represents the number of students picked up at that bus stop. The black dot in the center of the grid is the location of the school building.