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

Tyler Powell*

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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.

*Michigan State University, powel282@msu.edu. Thanks to Rene Crespin, Tasminda Dhaliwal, Todd Elder, Scott Imberman, and Salem Rogers for helpful comments and discussion. The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305B200009 to Michigan State University. The opinions expressed are those of the author and do not represent the views of the Institute or the U.S. Department of Education.

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.

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. While adults respond to longer commutes by reducing leisure time more than their younger counterparts, 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 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

[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.

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.

Two additional studies have calculated the actual lengths of students' school bus commutes within large urban districts.[4] Lincove and Valant (2018) use bus route pickup and dropoff times from school bus schedules in New Orleans to compare the nature of bus commutes to simulated commutes by car or public transit. They find that commuting by bus is slightly faster than commuting by public transit from the same location and much slower than commuting by car.

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. 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

[4]The only 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.

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 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 results for students can be applied to adult commutes.

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.

[6] Figures A1 and A2 show 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.

[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.

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 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, this substituted time comes 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

[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)

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 students 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.

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

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 Management System.[10] Implementing this system requires districts to keep consistent 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.

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,[11] these districts range from Rural: Distant to Suburb: Large, covering a variety of local contexts.[12] 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.[13] I drop 2020-21 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 and 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.

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

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

[11]https://nces.ed.gov/surveys/annualreports/topical-studies/locale/definitions

[12]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.

[13]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.

walking distances from November 2021. The distribution of pickup times underscores the importance of accounting for commutes when discussing early school start times.[14] 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 some ride for nearly two hours. Figure A5 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.[15] 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 data.[16] I construct behavior and attendance indicators from data on absences and suspensions. 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 grades.

[14] Figures A3 and A4 show that these distributions look quite similar for afternoon commutes, with some students dropped off at home as late as 5:00 PM.

[15] New Orleans is an exception. Lincove and Valant (2018) find that the median bus rider commutes for 35 minutes.

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

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 that are available to them. Table 1 details the characteristics of bus riders 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.

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. 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 an overall grade average based on the final percentage grade across all available, GPA-eligible high school courses for each academic year.[17] Finally, I define a

[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

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 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, estimates overstate the relationship between commuting distance to school 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. Even if parents were very attuned to a school's bus routes in a given year, they could not leverage this information in the housing market for the following year because routes can be redrawn each school year.

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

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

$RideTime_{it}$ 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 this idiosyncratic variation in commuting time from any residual variation driven by housing selection in augmented specifications. I use bus route fixed effects and home-to-school distance ring fixed effects to restrict comparisons to students with varied commutes whose families made similar housing and school choices.

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:

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

Finally, ω_{rt} is a bus route-by-year fixed effect, defined based on bus route ID numbers 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 this approach is that it allows for comparisons between students living close to the school and students living relatively far away. One way to account for remaining differences in housing selection is controlling for home-to-school walking distance in an augmented bus fixed effects model.

$$Y_{igrt} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \lambda SchDist_{it} + \omega_r + \delta_t + \mu_g + u_{igrt} \tag{3}$$

In this specification, I measure effects relative to other students riding the same bus conditional on the distance from each student's home to their school.

While bus route fixed effects allow for some comparisons within a bus route that I should avoid, they also rule out potentially useful comparisons between students who live close together and ride on different bus routes. For example, students along the blue and red routes in Figure 4 live geographically close to each other, but may face varied commutes on separate buses.

4.2 Distance Ring Fixed Effects

In addition to neighborhood choice, sorting into housing closer or farther from school could correlate with family characteristics that influence students' academic outcomes. Suppose that distance from home to school correlates with parents' educational engagement or socioeconomic status. In this case, it makes sense to make empirical comparisons only between students who live the same distance from the school. This comparison will also correct 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 restrict comparisons to students who live a similar distance from their school, 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 within the same, mile-wide band around the school with bins for 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 around a given school in the following specification:

$$Y_{igdt} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \psi_d + \delta_t + \mu_g + u_{igdt} \tag{4}$$

Here, I isolate ride time variation from factors other than home-to-school distance. This includes relatively exogenous variation such as assignment to a particular bus route or pickup order, but also less-exogenous variation which could influence commute time and housing choice. For example, if travel is slower to the north of the school because roads are not well-maintained, families would consider this commute impediment when selecting housing. Therefore, a 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 24 miles apart in the 9 to 12-mile distance ring may have selected housing based on different priorities.

4.3 Alternative Specifications

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. I estimate alternative specifications, with results reported in Section 5.4.

Bus route fixed effects control for neighborhood selection, but fail to account for distance to school. Distance ring effects 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. I estimate commute effects with distance ring by bus route fixed effects using the following specification:

$$Y_{igdrt} = \alpha + \beta RideTime_{it} + \gamma X_{it} + \psi_d \times \omega_r + \delta_t + \mu_g + u_{igdrt} \tag{5}$$

Within these distance-by-route groups, variation in ride times is limited, 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.

A more direct approach is to restrict directly 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. Census Blocks are larger in rural areas and suburbs than in densely populated urban areas. Therefore, this model may not sufficiently account for housing choices. 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.

Finally, 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.

Appendix B describes the within-group variation in ride times for each fixed effects restriction to motivate my model selection and contextualize these alternative results. Morning ride times vary substantially within bus routes and distance rings, but far less within Census blocks and distance ring-by-bus route groups.

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' attendance and behavior. 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.[18]

In Tables 2–5, Column 1 presents the results from a model with controls, but neither of the main fixed effects. Columns 3 and 5 report the main bus route fixed effects and distance ring fixed effects estimates from the specifications described in Sections 4.1 and 4.2. Columns 2 and 4 include a control for home-to-school walking distance. I prefer the specifications in Columns 4 and 5 which account for home-to-school walking distance.[19]

5.1 Effects on Attendance and Behavior

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 1.4–2.6 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 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 11.3–16.9 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 1.3–1.8 percent increase in non-bus suspensions) while afternoon commuting time crowds out other afternoon activities that could lead to suspension (a 1.4–2.2 percent decrease in non-bus suspensions).

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

[18] That is, for a better contextualization of magnitudes, estimates in Tables 2–5 and Tables A3–A10 should be scaled down by a factor of 2.8 and 2.6 for morning and afternoon commutes, respectively.

[19] Figure A6 plots the average share of economically disadvantaged students within each 3-mile home-to-school walking distance group.

ranges from -0.092 percentage points with bus route fixed effects to -0.125 percentage points with distance ring fixed effects. For a one standard deviation increase in afternoon commute, attendance rates fall by 0.03–0.05 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 seem to 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 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 and distance ring fixed effects (columns 3 and 5, respectively) 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 5 shows that having a longer morning commute leads to worse test scores, with no significant impacts from afternoon ride times. 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 marginally significant in the distance ring fixed effects specification.

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.[20] 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.[21]

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[22]—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 sections. Table A2 shows that commute length impacts students 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 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 4 reports the impacts of commuting time on average grades for high school students across all core classes 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 assign more work outside of the school day. 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. Together, the results on test scores and grades show that students' commuting time impacts their academic performance.

5.3 Heterogeneity

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 A9 and A12 plot the effects of morning commuting time separately by student race,

[20] 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 commutes.

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

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

sex, and economically disadvantaged status from the bus route fixed effect specification. Boys are particularly impacted by their commutes. 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.

5.4 Robustness

Tables A3 through A6 report the estimates from value added specifications which control for lagged outcomes. For behavioral outcomes, attendance, grades, and test scores, controlling for lagged outcomes has little impact on the estimated coefficients. Tables A7 through A10 show that using bus route and distance ring fixed effects together yields similar results to the main specifications. With Census Block fixed effects or interact 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.

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.[23] During the school year, children spend most 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,

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

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. Figures A13 and A14 show that this relationship is due to earlier wake-up times.[24] 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.[25] 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.[26] 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.

[24] Figures A15–A23 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.

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

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

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.[27] 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.

Still, 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).[28] I restrict to non-holiday Monday, Tuesday, Wednesday, and 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.

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.[29]

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

[27] 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.

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

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

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. 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 $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. Bus 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. 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.[30] 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.[31] Finally, bus maintenance costs average about $15,000 per year, per bus.[32] 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.

All bus riders at a school benefit from decreased commuting time when a school adds a 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

[30] 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

[31] 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

[32] 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

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 declines by 0.1–0.2 standard deviations or 2.2–4.4 minutes. If riders are evenly spread across all buses, adding a bus decreases the number of riders on each bus by 3.3. It is plausible that reducing the number of pickups by 3.3 riders decreases average ride times by more than 2.2 minutes, meaning that the benefit to students' future earnings outweighs the costs to the school.

6 Conclusion

Most public school students in North Carolina commute to school on school-provided buses. In rural areas where students are geographically disbursed, these commutes travel along indirect routes as schools minimize costs 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 are more impactful for 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. One potential policy response to long 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 benefits to students may outweigh the costs of adding a school bus.

My findings also inform the optimal design of transportation funding formulas. In many states, 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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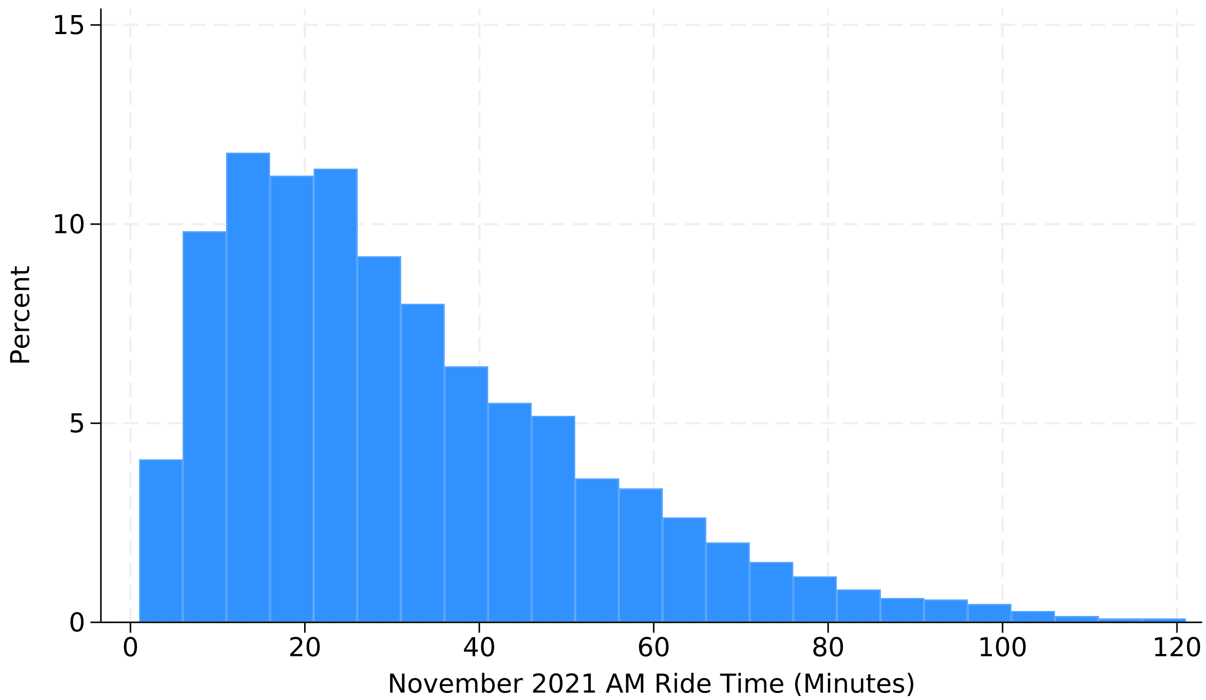
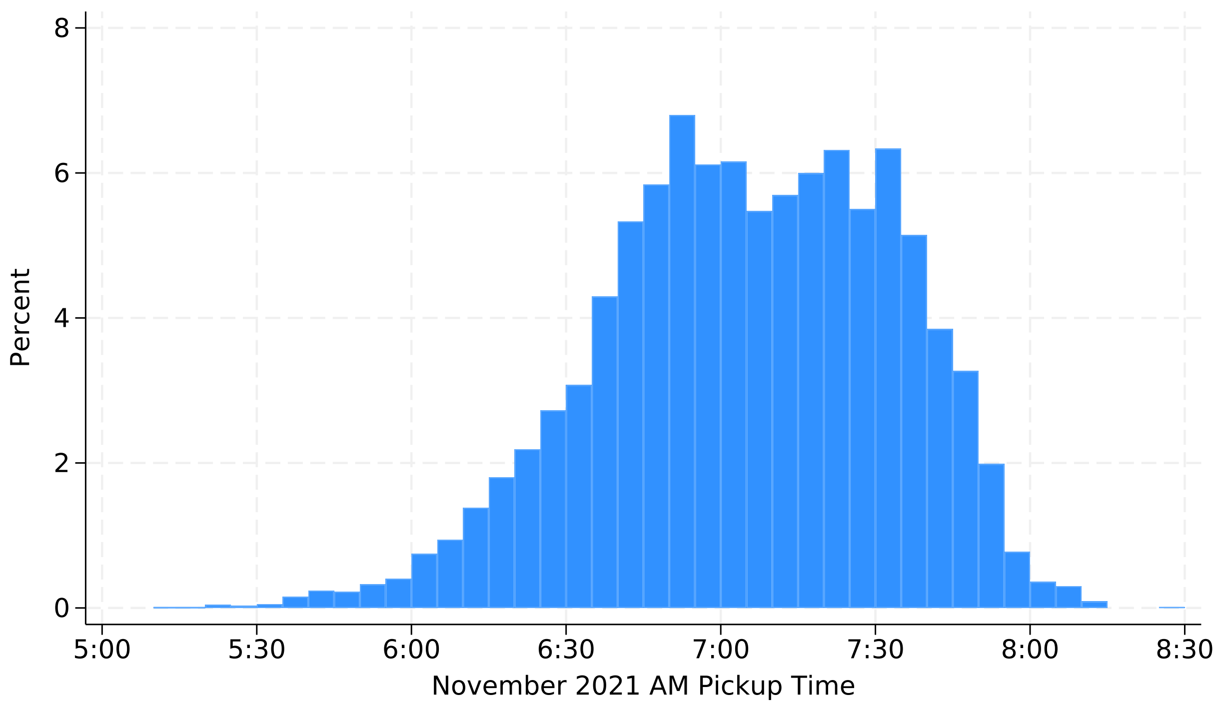
Figure 1: Characteristics of AM Bus Rides



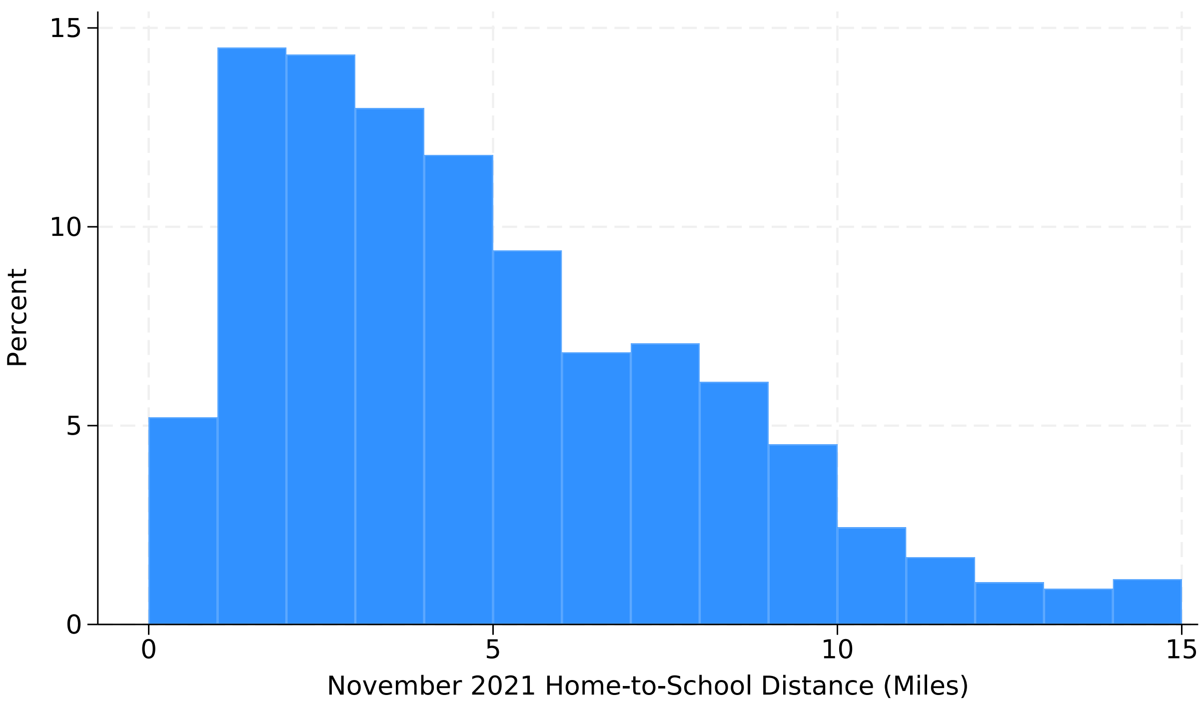
Percent calculated based on observations with non-missing attendance rates, race, and sex. This includes all riders in participating districts for the 2021-2022 school year.

Figure 2: Characteristics of AM Bus Rides



Percents calculated based on observations with non-missing attendance rates, race, and sex. This includes all riders in participating districts for the 2021-2022 school year.

Figure 3: Characteristics of AM Bus Rides



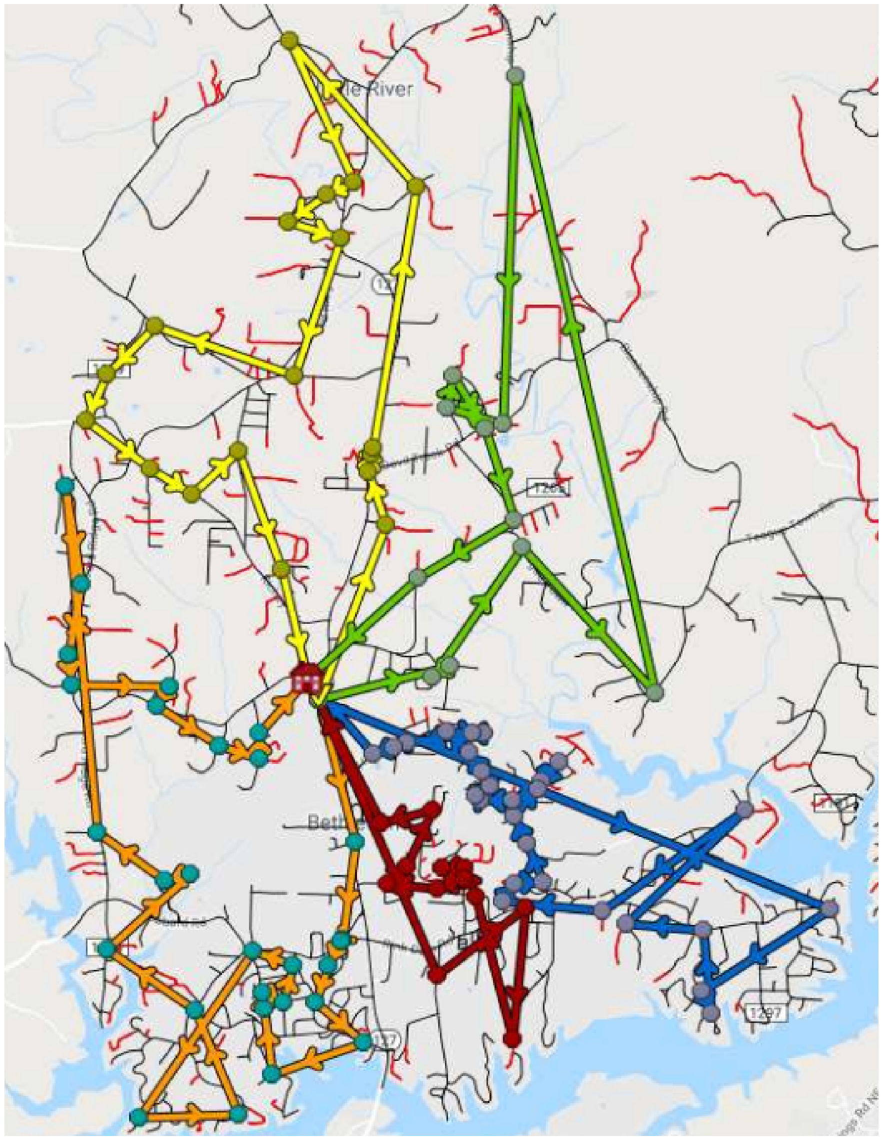
Percents calculated based on observations with non-missing attendance rates, race, and sex. This includes all riders in participating districts for the 2021-2022 school year.

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	5
			Any Suspension		
AM Ride Time (Hours)	0.008***	0.007**	0.010***	0.011***	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.002	-0.004	-0.000	-0.000	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Outcome Mean	0.151	0.151	0.151	0.151	0.151
N	296545	296179	295387	295194	296289
			Bus Suspension		
AM Ride Time (Hours)	0.006***	0.003	0.007***	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.011***	0.008***	0.012***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.027	0.027	0.027	0.027	0.027
N	296545	296335	295387	295194	296289
			Non-Bus Suspension		
AM Ride Time (Hours)	0.005*	0.006*	0.007**	0.009***	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.007**	-0.007**	-0.005**	-0.004	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Outcome Mean	0.137	0.137	0.137	0.137	0.137
N	296545	296335	295387	295194	296289
Controls					
Home-to-School Walking Distance		X		X	
Fixed Effects					
Bus Route			X	X	
Distance Ring					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	5
			Attendance Rate		
AM Ride Time (Hours)	-0.166***	-0.082	-0.012	0.018	-0.087*
	(0.050)	(0.052)	(0.048)	(0.050)	(0.049)
PM Ride Time (Hours)	-0.153***	-0.080*	-0.125***	-0.098**	-0.092**
	(0.048)	(0.046)	(0.045)	(0.043)	(0.046)
Outcome Mean	94.948	94.948	94.953	94.953	94.948
N	296545	296335	295387	295194	296289
			Chronic Absenteeism		
AM Ride Time (Hours)	0.008***	0.005*	0.001	0.000	0.005*
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
PM Ride Time (Hours)	0.006**	0.003	0.005**	0.004*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.114	0.114	0.114	0.114	0.114
N	296545	296335	295387	295194	296289
Controls					
Home-to-School Walking Distance		X		X	
Fixed Effects					
Bus Route			X	X	
Distance Ring					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: Grade Results

	1	2	3	4	5
	Core Subject Grades				
AM Ride Time (Hours)	-0.357*	-0.267	-0.181	-0.193	-0.183
	(0.204)	(0.205)	(0.201)	(0.208)	(0.202)
PM Ride Time (Hours)	-0.394*	-0.317	-0.331	-0.343	-0.242
	(0.225)	(0.229)	(0.210)	(0.215)	(0.212)
Outcome Mean	80.197	80.193	80.165	80.163	80.192
N	87200	87080	86395	86292	87059
	Math and Science Grades				
AM Ride Time (Hours)	-0.310*	-0.191	-0.199	-0.205	-0.110
	(0.184)	(0.192)	(0.204)	(0.217)	(0.186)
PM Ride Time (Hours)	-0.527**	-0.425*	-0.453*	-0.468*	-0.352
	(0.238)	(0.249)	(0.240)	(0.252)	(0.241)
Outcome Mean	79.330	79.327	79.294	79.292	79.326
N	83753	83640	82990	82893	83623
Controls					
Home-to-School Walking Distance		X		X	
Fixed Effects					
Bus Route			X	X	
Distance Ring					X

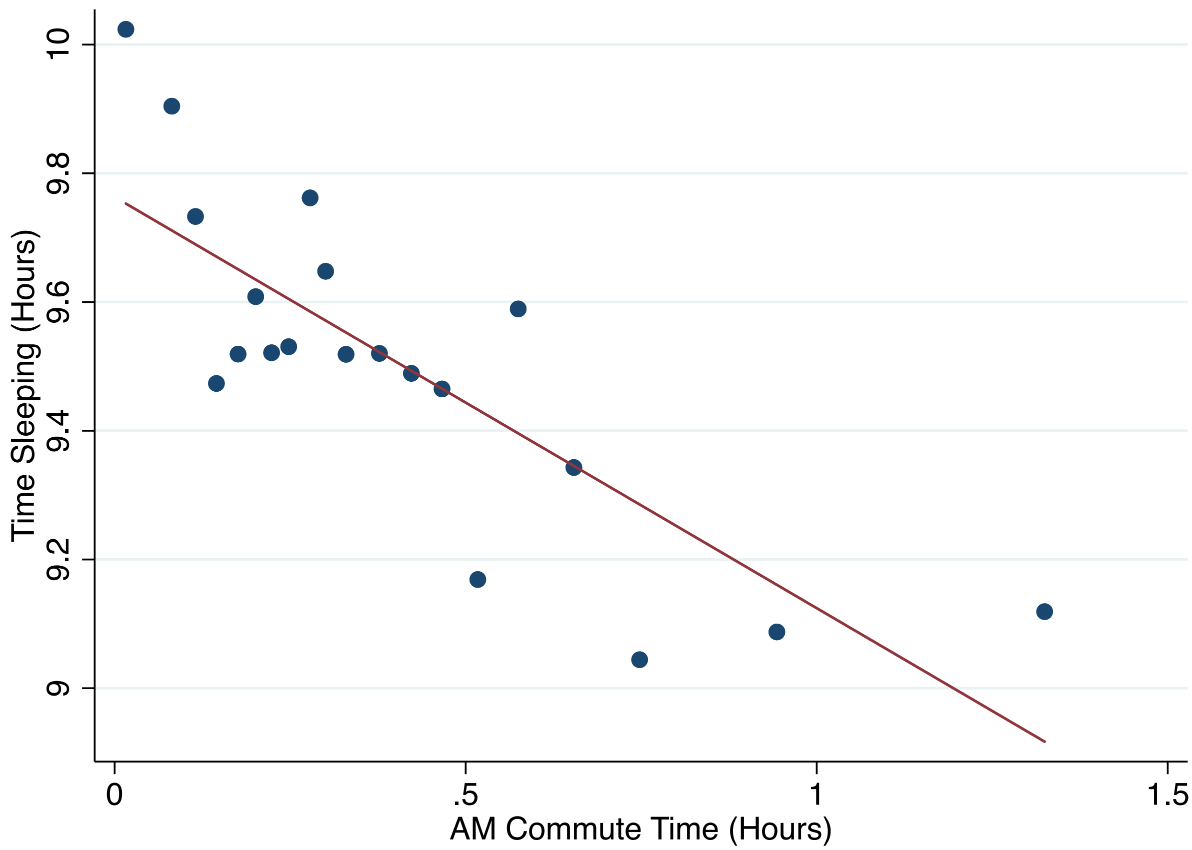
Grades are calculated as the average of all GPA-eligible final grades in an academic year. Core subjects are Math, Science, ELA, and Social Studies. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects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

Table 5: Testing Results

	1	2	3	4	5
	End-of-Grade Math (3–8)				
AM Ride Time (Hours)	-0.025**	-0.029***	-0.022*	-0.027**	-0.026**
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
PM Ride Time (Hours)	-0.007	-0.011	-0.001	-0.005	-0.004
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Outcome Mean	0.092	0.092	0.093	0.093	0.092
N	111492	111452	111184	111143	111400
	End-of-Grade Reading (3–8)				
AM Ride Time (Hours)	-0.019*	-0.024**	-0.013	-0.015	-0.018*
	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)
PM Ride Time (Hours)	-0.002	-0.005	0.004	0.002	-0.000
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Outcome Mean	0.096	0.096	0.098	0.098	0.096
N	107677	107635	107383	107340	107584
	ACT Composite				
AM Ride Time (Hours)	-0.038**	-0.053***	-0.047*	-0.051*	-0.038**
	(0.019)	(0.018)	(0.024)	(0.026)	(0.017)
PM Ride Time (Hours)	-0.005	-0.018	0.003	-0.002	-0.011
	(0.021)	(0.023)	(0.031)	(0.032)	(0.023)
Outcome Mean	-0.188	-0.189	-0.199	-0.200	-0.190
N	11465	11436	11094	11071	11418
Controls					
Home-to-School Walking Distance		X		X	
Fixed Effects					
Bus Route			X	X	
Distance Ring					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. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

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)

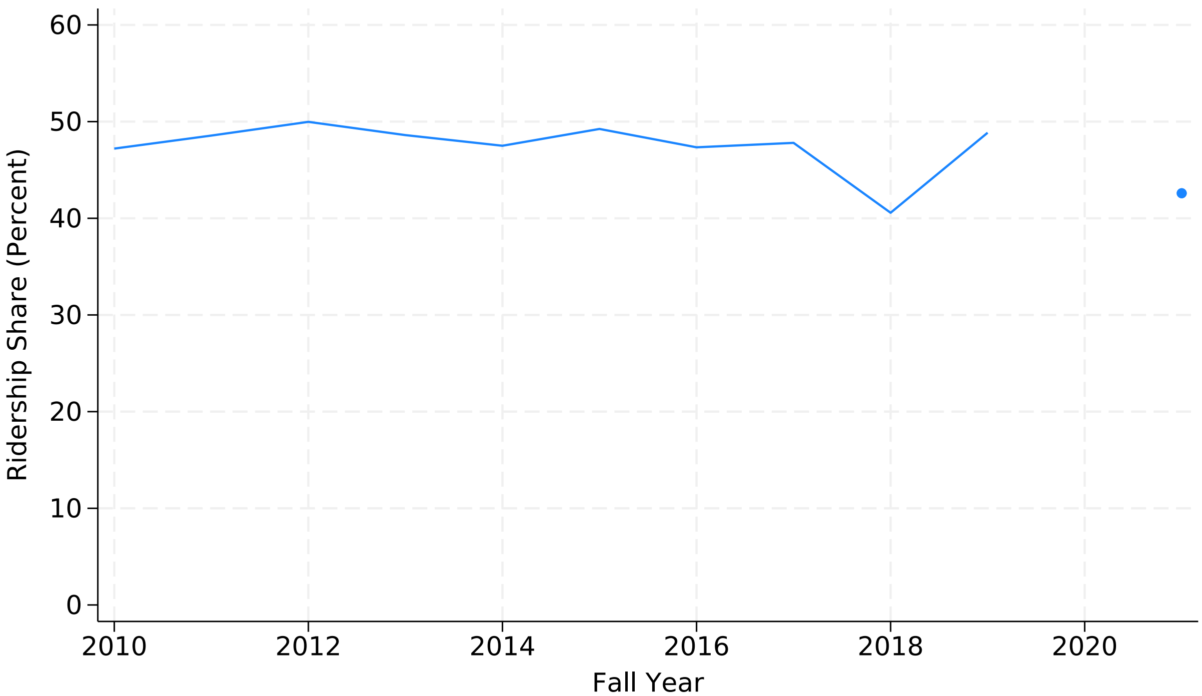
Table 6: Time Use Results

	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.

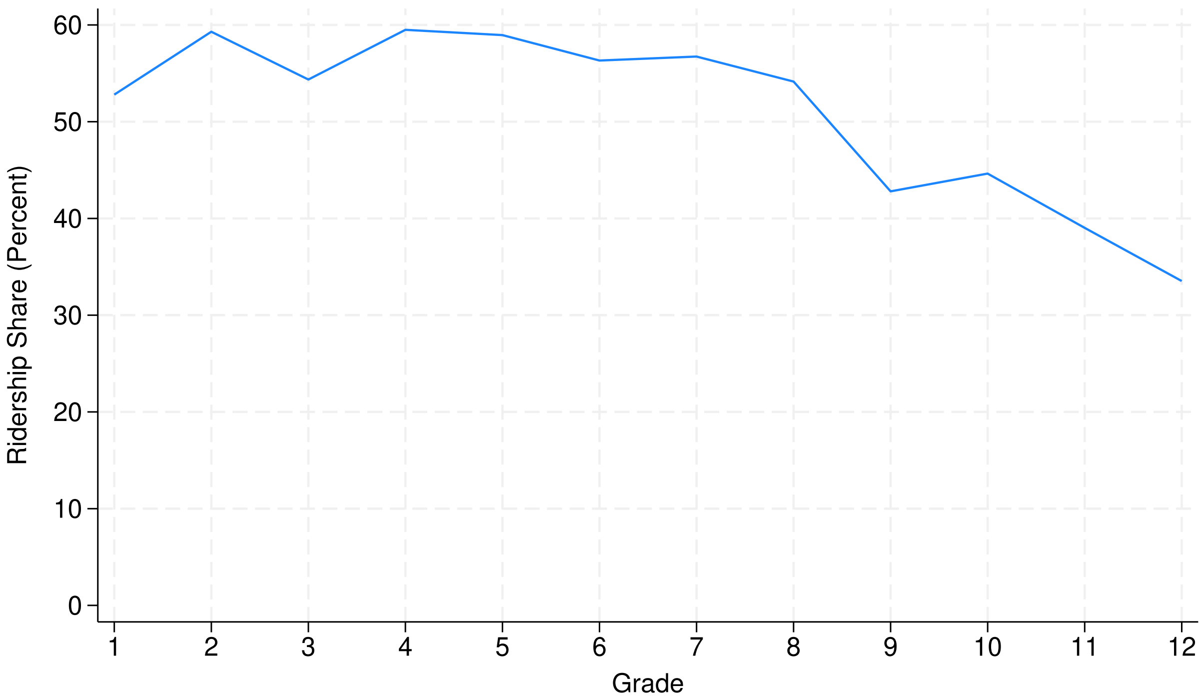
Appendix A Figures and Tables

Figure A1: Sample Ridership Rates



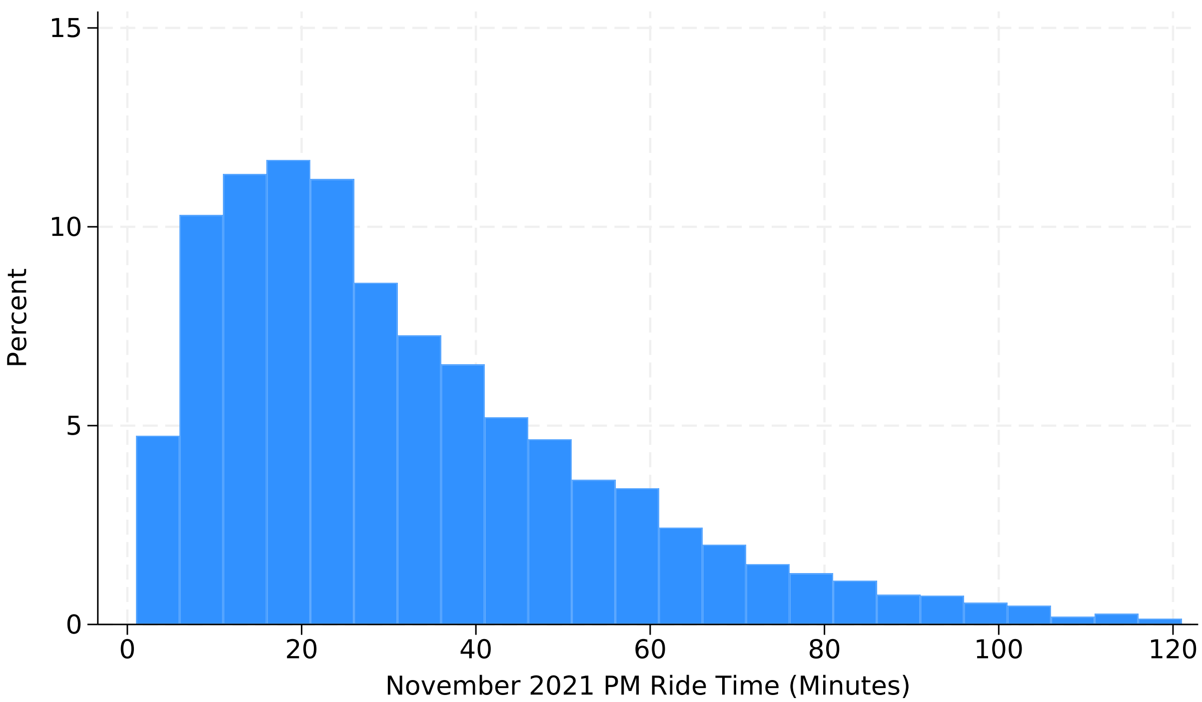
Ridership share is defined as the number of bus riders divided by the total number of students with positive attendance rates.

Figure A2: Sample Ridership Rates



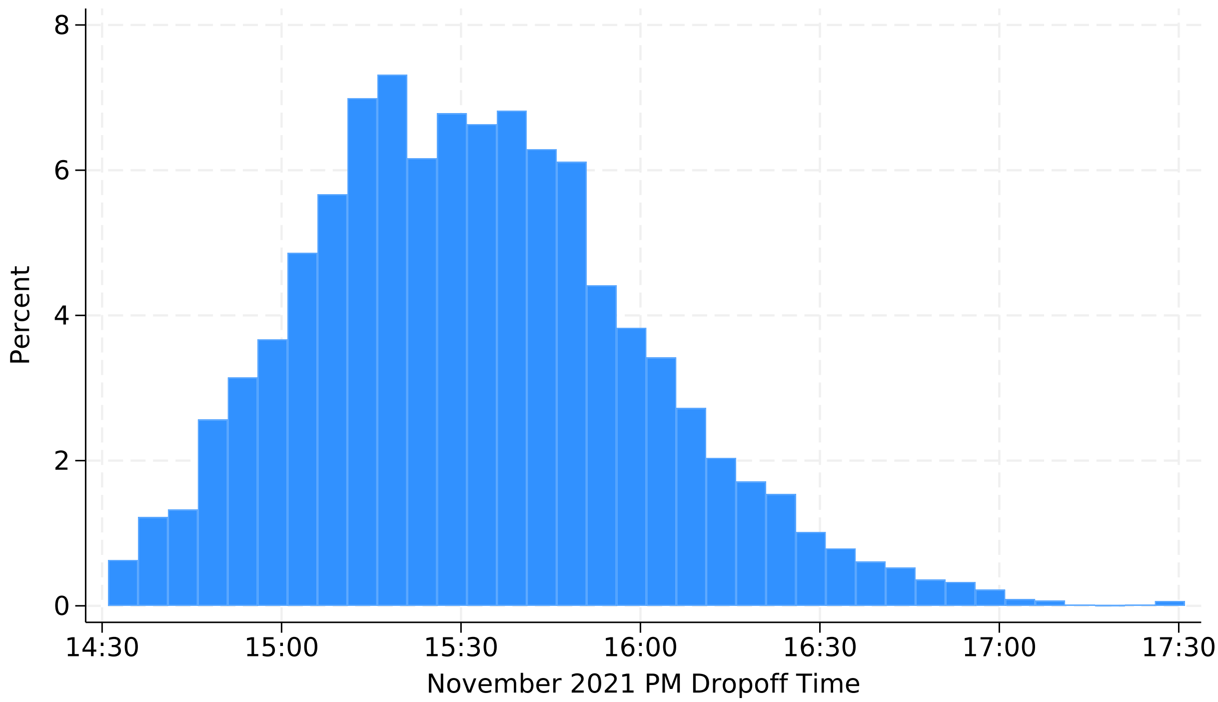
Ridership share is defined as the number of bus riders divided by the total number of students with positive attendance rates.

Figure A3: Characteristics of PM Bus Commutes



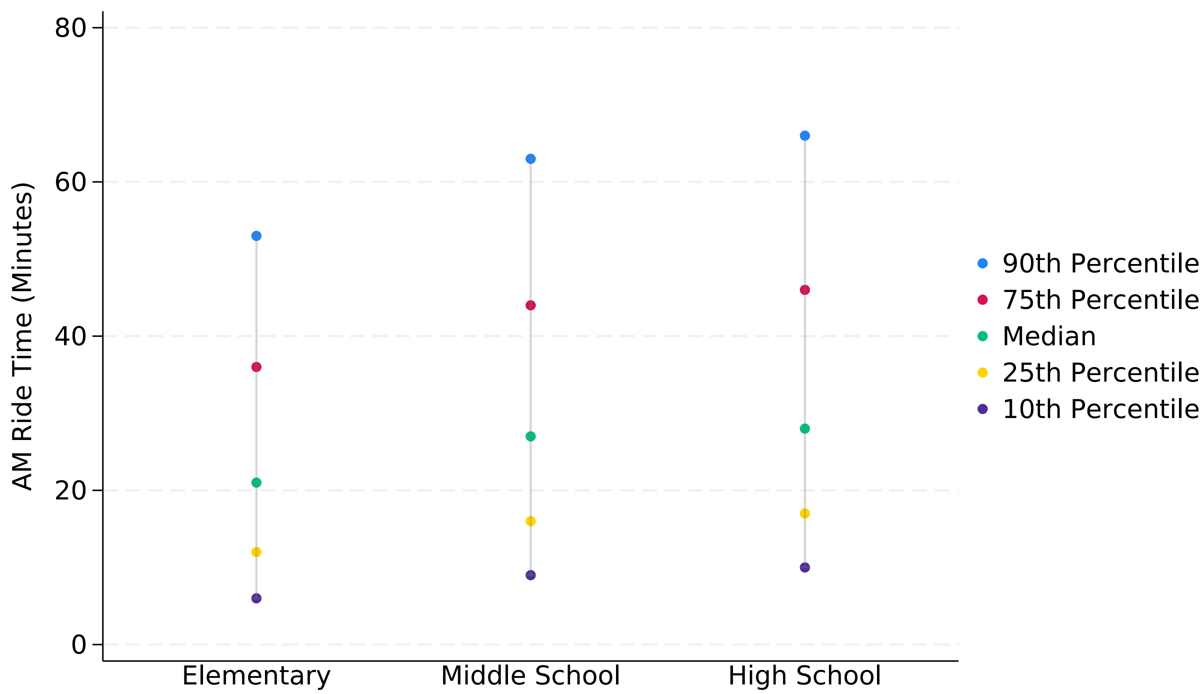
Percent calculated based on observations with non-missing attendance rates, race, and sex. This includes all riders in participating districts for the 2021-2022 school year.

Figure A4: Characteristics of PM Bus Commutes



Percent calculated based on observations with non-missing attendance rates, race, and sex. This includes all riders in participating districts for the 2021-2022 school year.

Figure A5: Distribution of AM Bus Ride Times by Grade Level



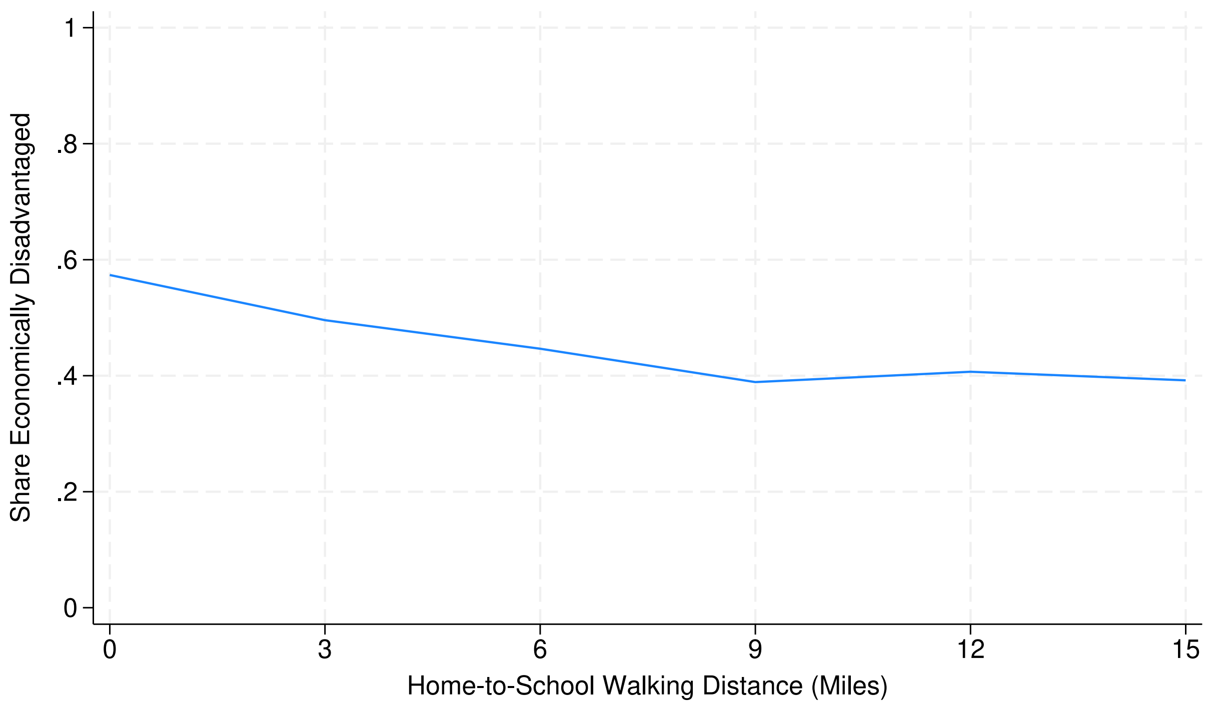
Elementary school is defined as grades K–5, Middle School is defined as grades 6–8, and High School is defined as grades 9–12. Percentiles are calculated based on all available years of data in the participating districts.

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.

Figure A6: Socioeconomic Status by Distance from School



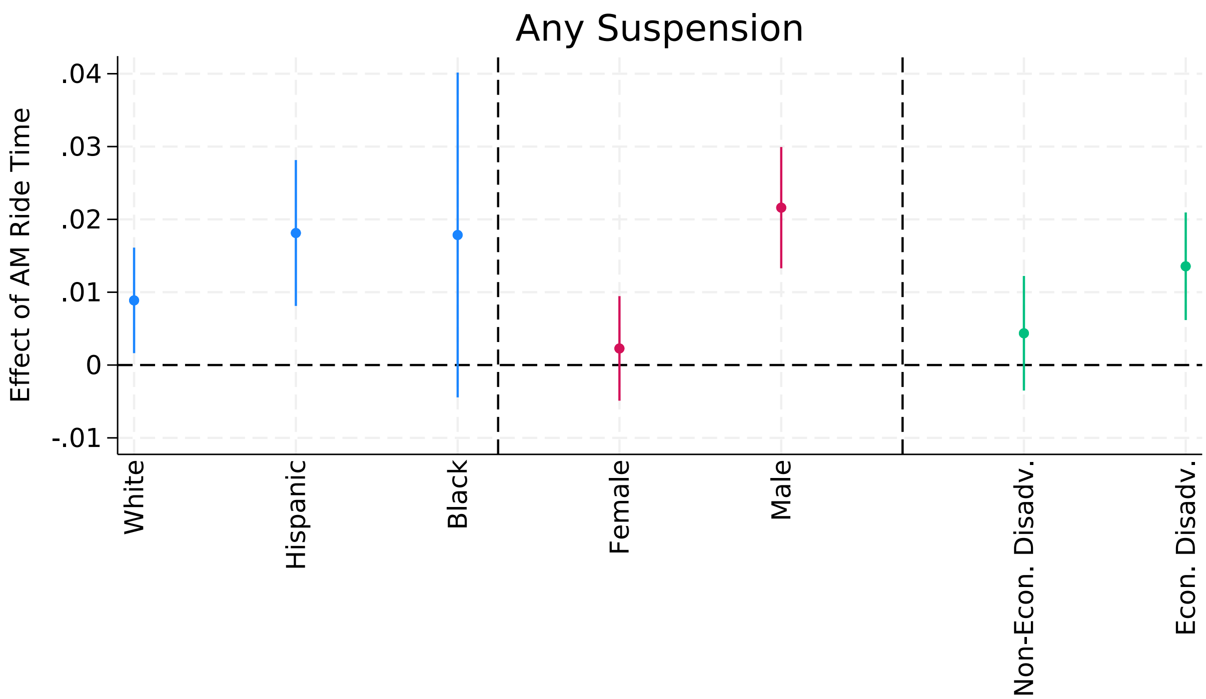
I calculate the share of economically disadvantaged students for each three-mile home-to-school walking distance ring among students who ride the bus in the morning and afternoon.

Table A2: 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				

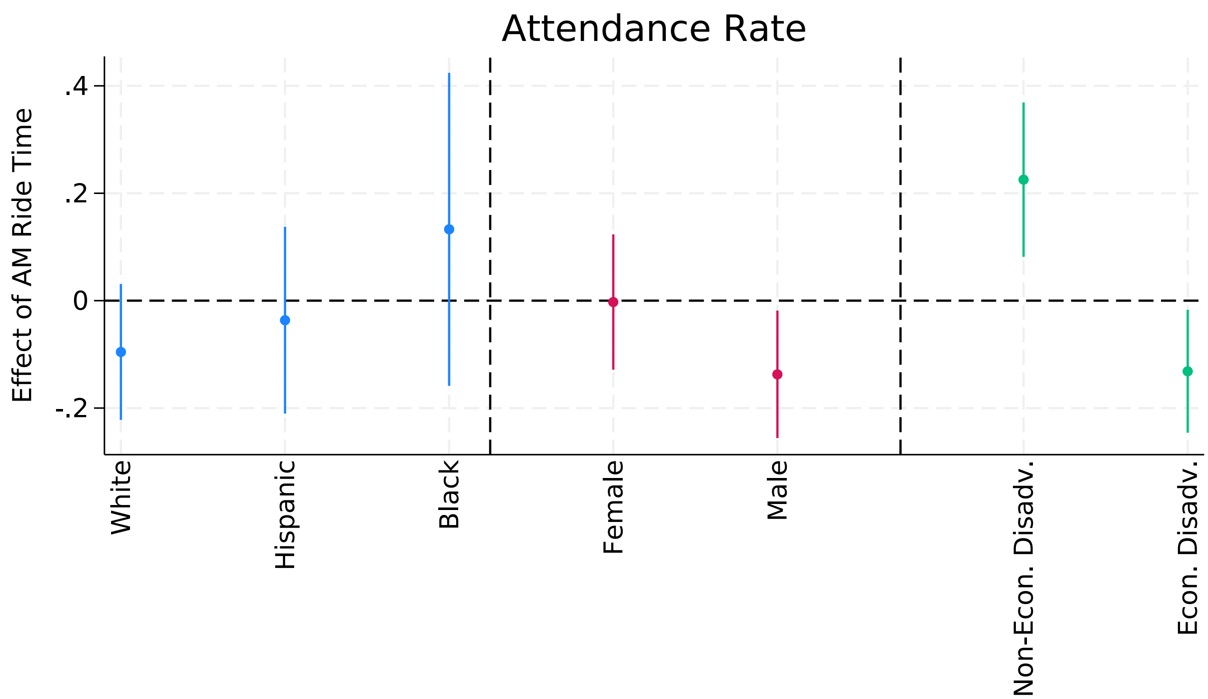
ACT sections are taken in a fixed order: English, Math, 10-minute break, Reading, and Science. Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language 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 A7: Effect Heterogeneity—Behavior



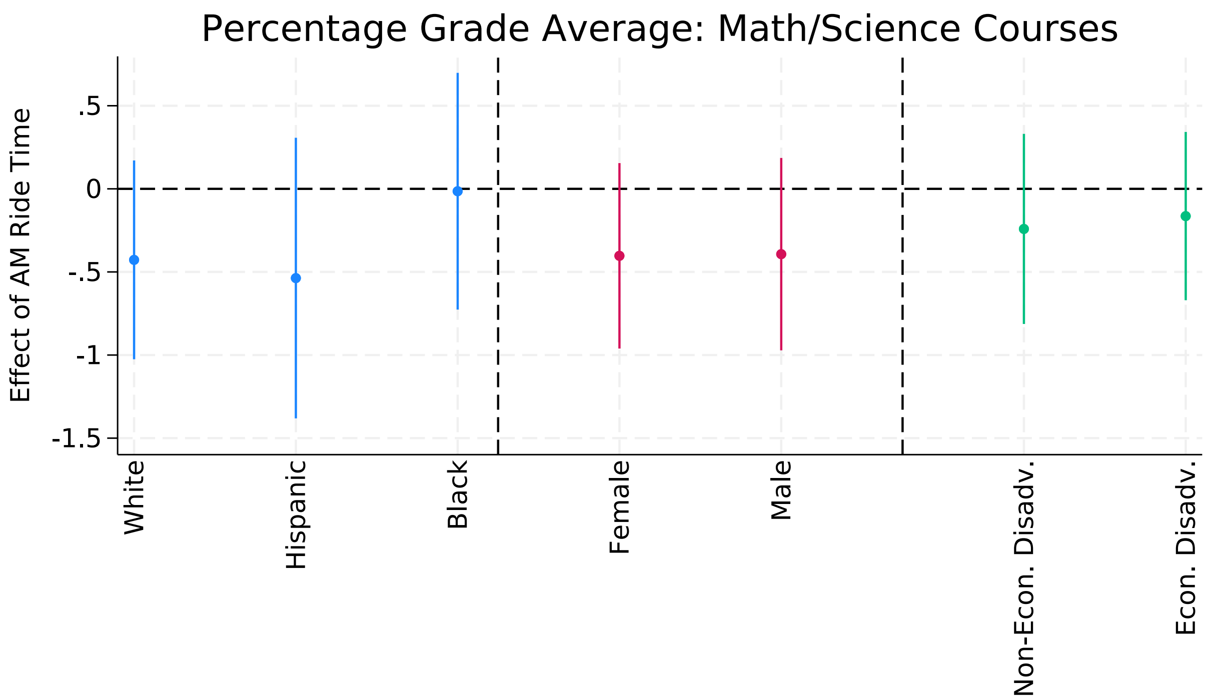
All students who appear in the attendance panel, but do not appear in the suspension records are assumed to have zero suspensions. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school 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: Effect Heterogeneity—Attendance



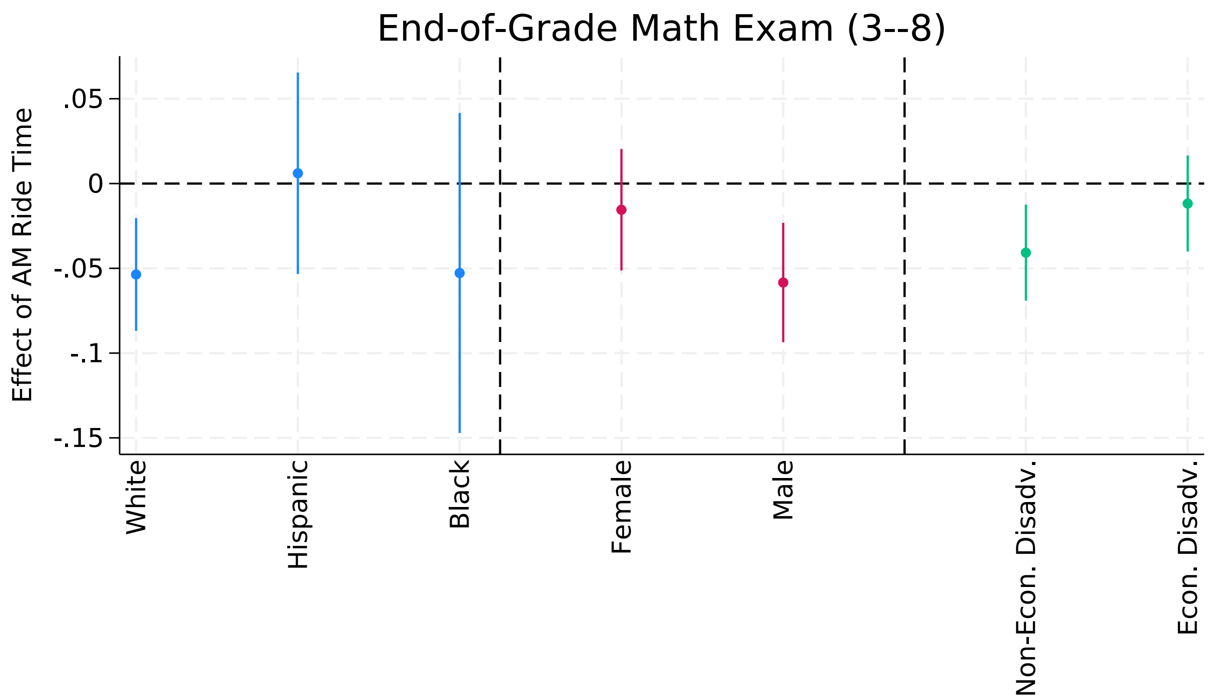
Attendance rate is defined as 100*(days enrolled - days absent)/days enrolled. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification includes 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: Effect Heterogeneity—Grades



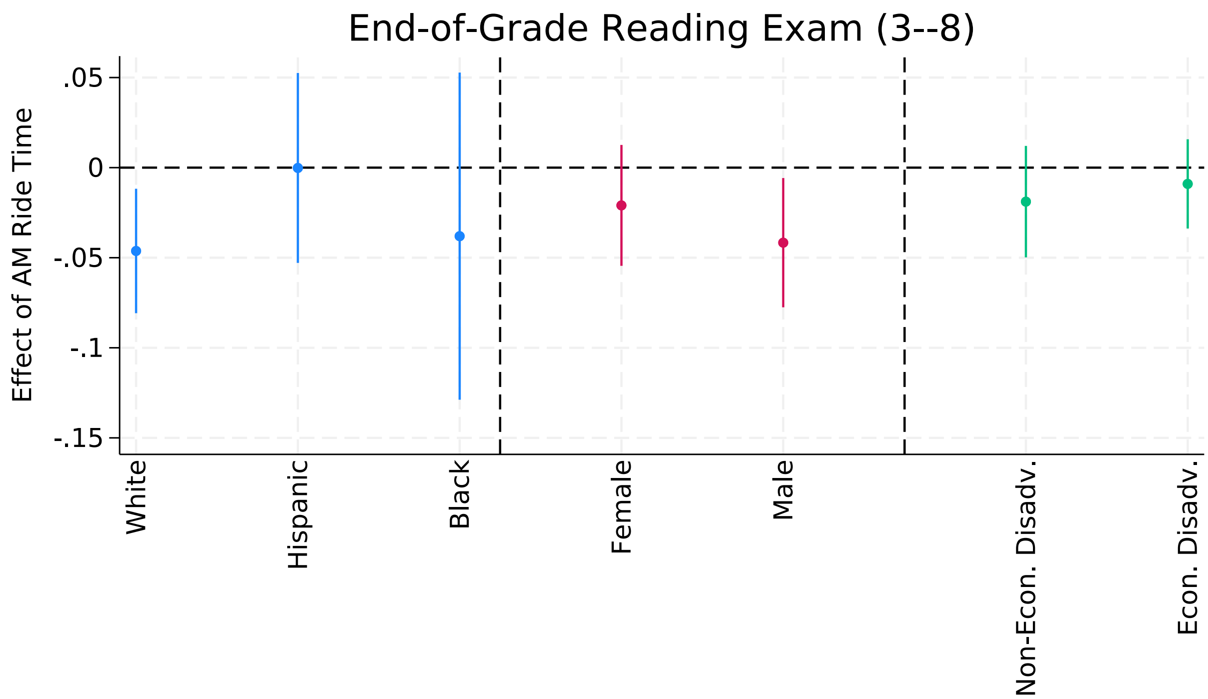
Grades are calculated as the average of all GPA-eligible final grades in an academic year. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking distance. Each specification 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 A10: Testing Effect Heterogeneity—End-of-Grade Math



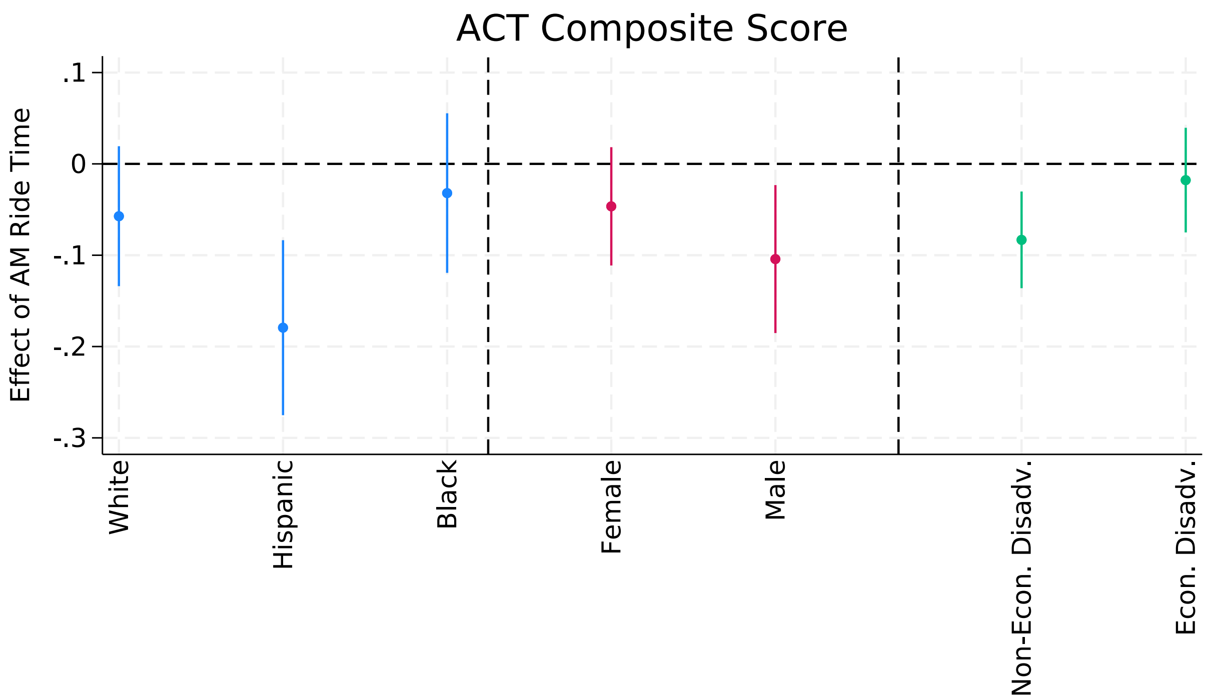
Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Results from the bus route fixed effects specification. Control variables include race, sex, disability status, gifted status, English language learner status, and home-to-school walking 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 A11: Testing Effect Heterogeneity—End-of-Grade Reading



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 A12: Testing Effect Heterogeneity—ACT



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 A3: Behavior Results—Value Added

	1	2	3	4	5
			Any Suspension		
AM Ride Time (Hours)	0.007***	0.006**	0.009***	0.008***	0.006**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.002	-0.002	-0.000	-0.001	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Outcome Mean	0.152	0.152	0.152	0.152	0.152
N	291588	291378	290427	290234	291332
			Bus Suspension		
AM Ride Time (Hours)	0.005***	0.002	0.006***	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.010***	0.007***	0.011***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Outcome Mean	0.027	0.027	0.027	0.027	0.027
N	291588	291378	290427	290234	291332
			Non-Bus Suspension		
AM Ride Time (Hours)	0.005*	0.006**	0.006**	0.007***	0.005*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
PM Ride Time (Hours)	-0.006**	-0.006**	-0.005**	-0.004*	-0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.137	0.137	0.137	0.137	0.137
N	291588	291378	290427	290234	291332
Controls					
Home-to-School Walking Distance		X		X	
Lagged Outcome	X	X	X	X	X
Fixed Effects					
Bus Route			X	X	
Distance Ring					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 A4: Attendance Results—Value Added

	1	2	3	4	5
	Attendance Rate				
AM Ride Time (Hours)	-0.080**	-0.026	0.013	0.018	-0.031
	(0.038)	(0.040)	(0.033)	(0.050)	(0.039)
PM Ride Time (Hours)	-0.102***	-0.057**	-0.094***	-0.098**	-0.066**
	(0.030)	(0.029)	(0.032)	(0.043)	(0.030)
Outcome Mean	94.924	94.924	94.929	94.953	94.924
N	291588	291378	290427	295194	291332
	Chronic Absenteeism				
AM Ride Time (Hours)	0.004*	0.001	-0.002	-0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM Ride Time (Hours)	0.005***	0.003	0.006***	0.005**	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Outcome Mean	0.114	0.114	0.114	0.114	0.114
N	291588	291378	290427	290234	291332
Controls					
Home-to-School Walking Distance		X		X	
Lagged Outcome	X	X	X	X	X
Fixed Effects					
Bus Route			X	X	
Distance Ring					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 A5: Grade Results—Value Added

	1	2	3	4	5
	Core Subject Grades				
AM Ride Time (Hours)	-0.139	-0.103	0.025	0.027	-0.090
	(0.130)	(0.147)	(0.109)	(0.118)	(0.168)
PM Ride Time (Hours)	-0.338**	-0.309*	-0.047	-0.049	-0.248
	(0.156)	(0.164)	(0.123)	(0.129)	(0.165)
Outcome Mean	80.080	80.077	80.050	80.047	80.076
N	59885	59809	59245	59180	59798
	Math and Science Grades				
AM Ride Time (Hours)	-0.119	-0.070	-0.130	-0.133	-0.066
	(0.139)	(0.172)	(0.136)	(0.163)	(0.192)
PM Ride Time (Hours)	-0.418**	-0.383**	-0.123	-0.145	-0.325*
	(0.175)	(0.187)	(0.153)	(0.178)	(0.188)
Outcome Mean	79.194	79.192	79.154	79.152	79.193
N	56528	56460	55896	55840	56450
Controls					
Home-to-School Walking Distance		X		X	
Lagged Outcome	X	X	X	X	X
Fixed Effects					
Bus Route			X	X	
Distance Ring					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 A6: Testing Results—Value Added

	1	2	3	4	5
			End-of-Grade Math (3–8)		
AM Ride Time (Hours)	-0.013**	-0.012*	-0.013**	-0.014**	-0.009
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
PM Ride Time (Hours)	0.003	0.004	0.005	0.004	0.007
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Outcome Mean	0.138	0.138	0.140	0.139	0.138
N	84657	84629	84391	84363	84575
			End-of-Grade Reading (3–8)		
AM Ride Time (Hours)	-0.006	-0.008	-0.007	-0.005	-0.006
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
PM Ride Time (Hours)	0.003	0.001	0.004	0.006	0.005
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Outcome Mean	0.147	0.147	0.148	0.148	0.147
N	81225	81193	80954	80922	81142
Controls					
Home-to-School Walking Distance		X		X	
Lagged Outcome	X	X	X	X	X
Fixed Effects					
Bus Route			X	X	
Distance Ring					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: Behavior Results—Robustness

	1	2	3
	Any Suspension		
AM Ride Time (Hours)	0.010***	0.010**	0.008
	(0.003)	(0.004)	(0.006)
PM Ride Time (Hours)	-0.001	-0.004	-0.001
	(0.003)	(0.003)	(0.005)
Outcome Mean	0.151	0.151	0.144
N	295143	289555	145791
	Bus Suspension		
AM Ride Time (Hours)	0.004**	0.004**	0.010**
	(0.002)	(0.002)	(0.004)
PM Ride Time (Hours)	0.008***	0.009***	0.003
	(0.002)	(0.002)	(0.003)
Outcome Mean	0.027	0.027	0.029
N	295143	289555	145791
	Non-Bus Suspension		
AM Ride Time (Hours)	0.007**	0.007**	0.002
	(0.003)	(0.004)	(0.007)
PM Ride Time (Hours)	-0.005*	-0.008**	-0.002
	(0.003)	(0.003)	(0.005)
Outcome Mean	0.137	0.137	0.129
N	295143	289555	145791
Fixed Effects			
Bus Route	X		
Distance Ring	X		
Bus Route X Distance Ring		X	
Census Block			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 A8: Attendance Results—Robustness

	1	2	3
	Attendance Rate		
AM Ride Time (Hours)	0.003	0.038	-0.083
	(0.051)	(0.063)	(0.068)
PM Ride Time (Hours)	-0.095**	-0.069	-0.063
	(0.045)	(0.056)	(0.058)
Outcome Mean	94.953	94.967	95.837
N	295143	289555	145791
	Chronic Absenteeism		
AM Ride Time (Hours)	-0.000	0.000	0.004
	(0.003)	(0.003)	(0.004)
PM Ride Time (Hours)	0.004*	0.004	-0.002
	(0.002)	(0.003)	(0.004)
Outcome Mean	0.114	0.113	0.071
N	295143	289555	145791
Fixed Effects			
Bus Route	X		
Distance Ring	X		
Bus Route X Distance Ring		X	
Census Block			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. Standard errors are clustered at the school level. * p<0.10; ** p<0.05; *** p<0.01.

Table A9: Grade Results—Robustness

	1	2	3
	Core Subject Grades		
AM Ride Time (Hours)	-0.081	-0.087	-0.207
	(0.200)	(0.247)	(0.242)
PM Ride Time (Hours)	-0.267	-0.375	-0.291
	(0.208)	(0.265)	(0.333)
Outcome Mean	80.162	80.129	81.347
N	86274	84205	41167
	Math and Science Grades		
AM Ride Time (Hours)	-0.087	-0.064	-0.153
	(0.195)	(0.235)	(0.208)
PM Ride Time (Hours)	-0.382	-0.478	-0.344
	(0.241)	(0.291)	(0.389)
Outcome Mean	79.291	79.258	80.493
N	82876	80871	39789
Fixed Effects			
Bus Route	X		
Distance Ring	X		
Bus Route X Distance Ring		X	
Census Block			X

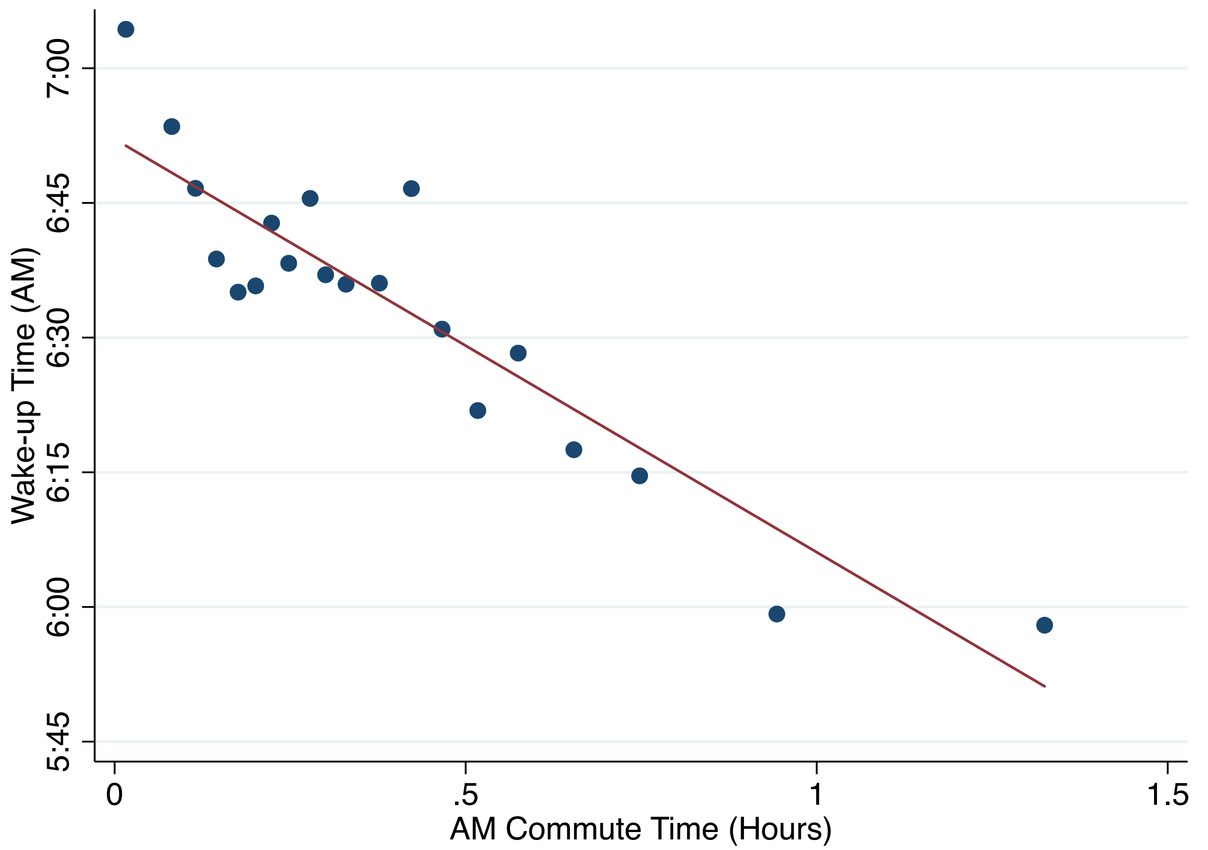
Grades are calculated as the average of all GPA-eligible final grades in an academic year. Core subjects are Math, Science, ELA, and Social Studies. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects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

Table A10: Testing Sample—Robustness

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

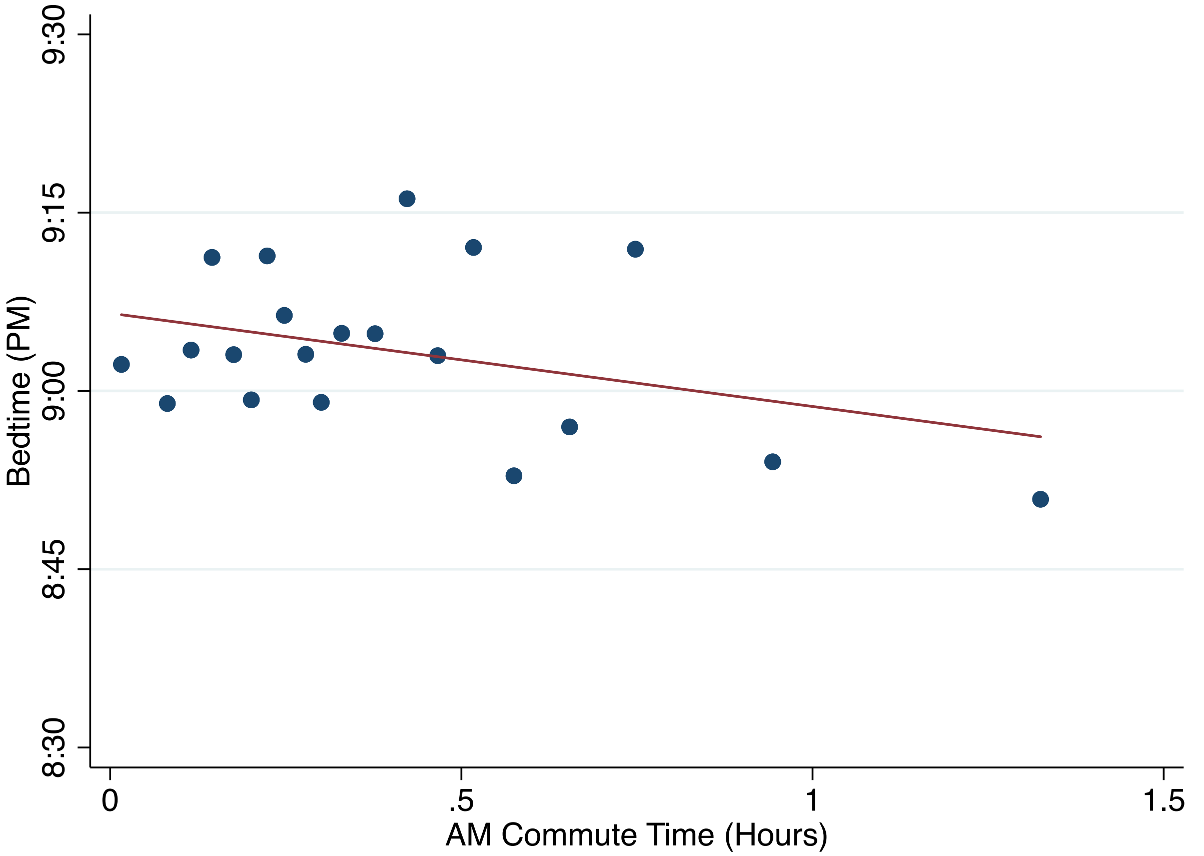
Test scores are standardized at the test-by-grade-by-year level across all public school students in North Carolina. Control variables also include race, sex, disability status, gifted status, and English language learner status. Each specification includes fixed effects for school, grade, and year.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

Figure A13: Morning Commute Time versus Sleep



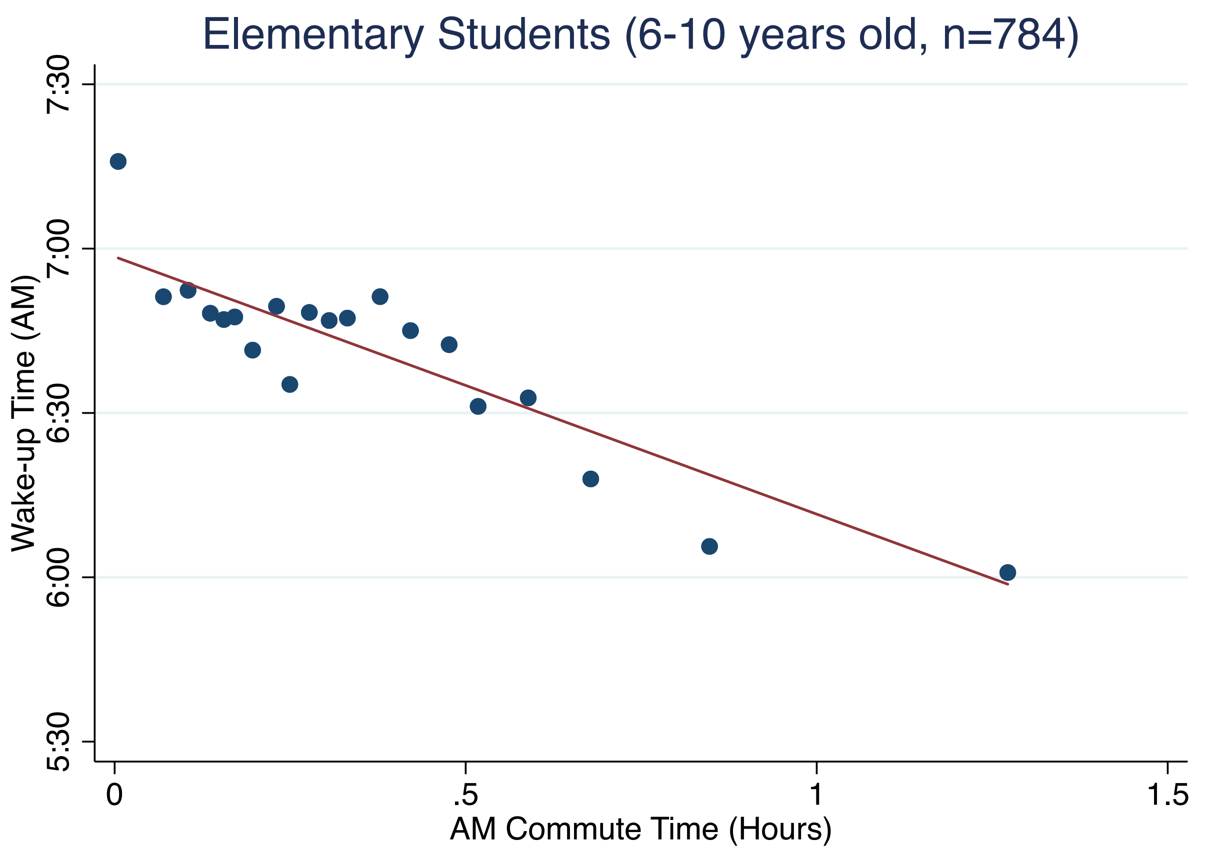
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional on age, sex, and family income. The sample includes one observation per student and is restricted to observations that occur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

Figure A14: Morning Commute Time versus Sleep



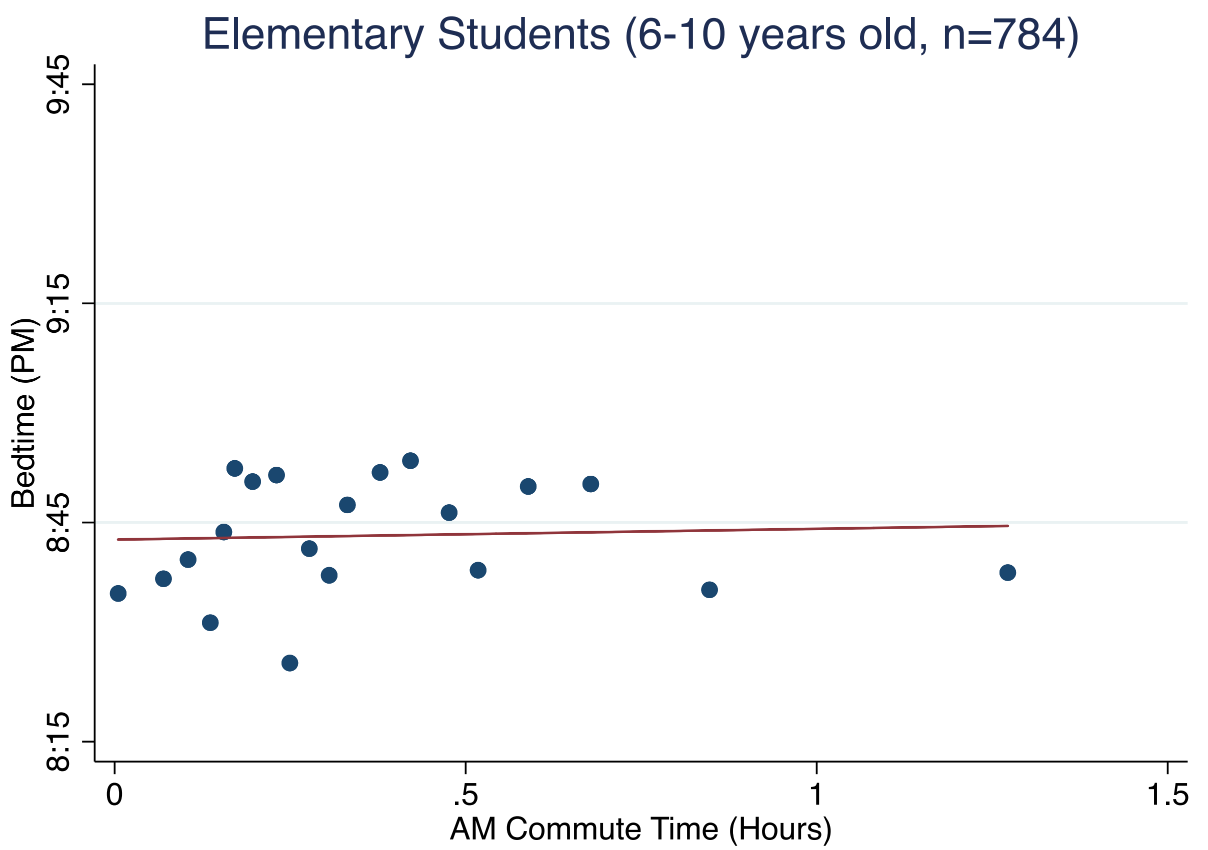
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional on age, sex, and family income. The sample includes one observation per student and is restricted to observations that occur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

Figure A15: Morning Commute Time versus Sleep – Elementary Students



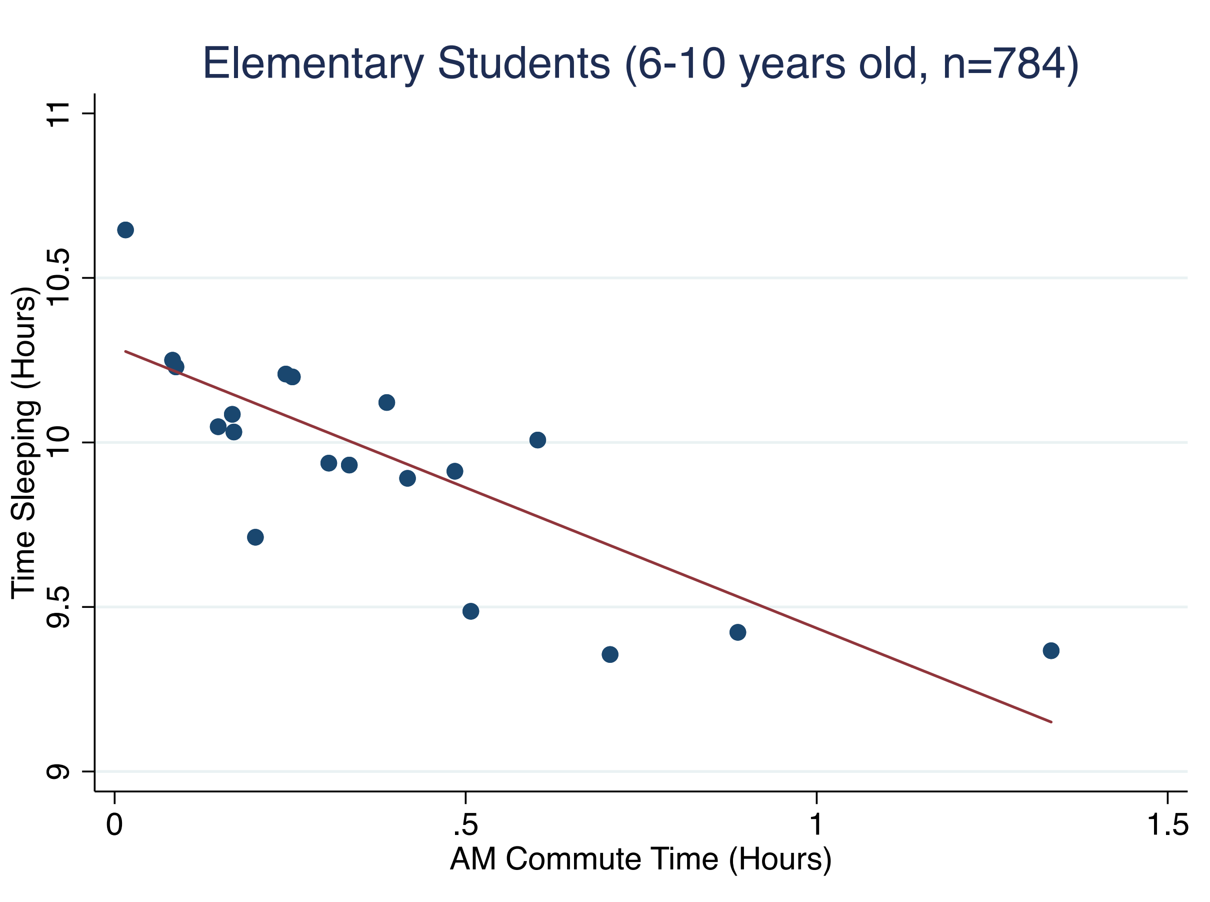
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A16: Morning Commute Time versus Sleep – Elementary Students



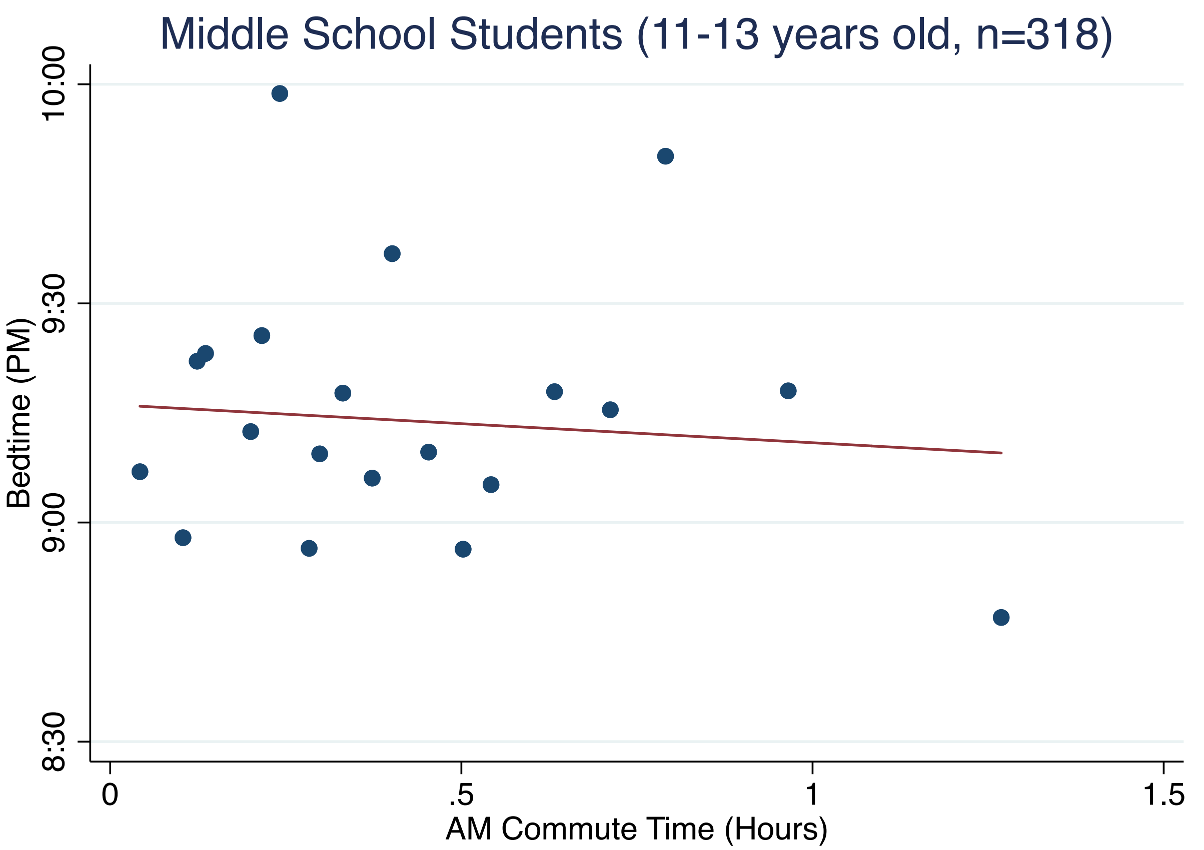
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A17: Morning Commute Time versus Sleep – Elementary Students



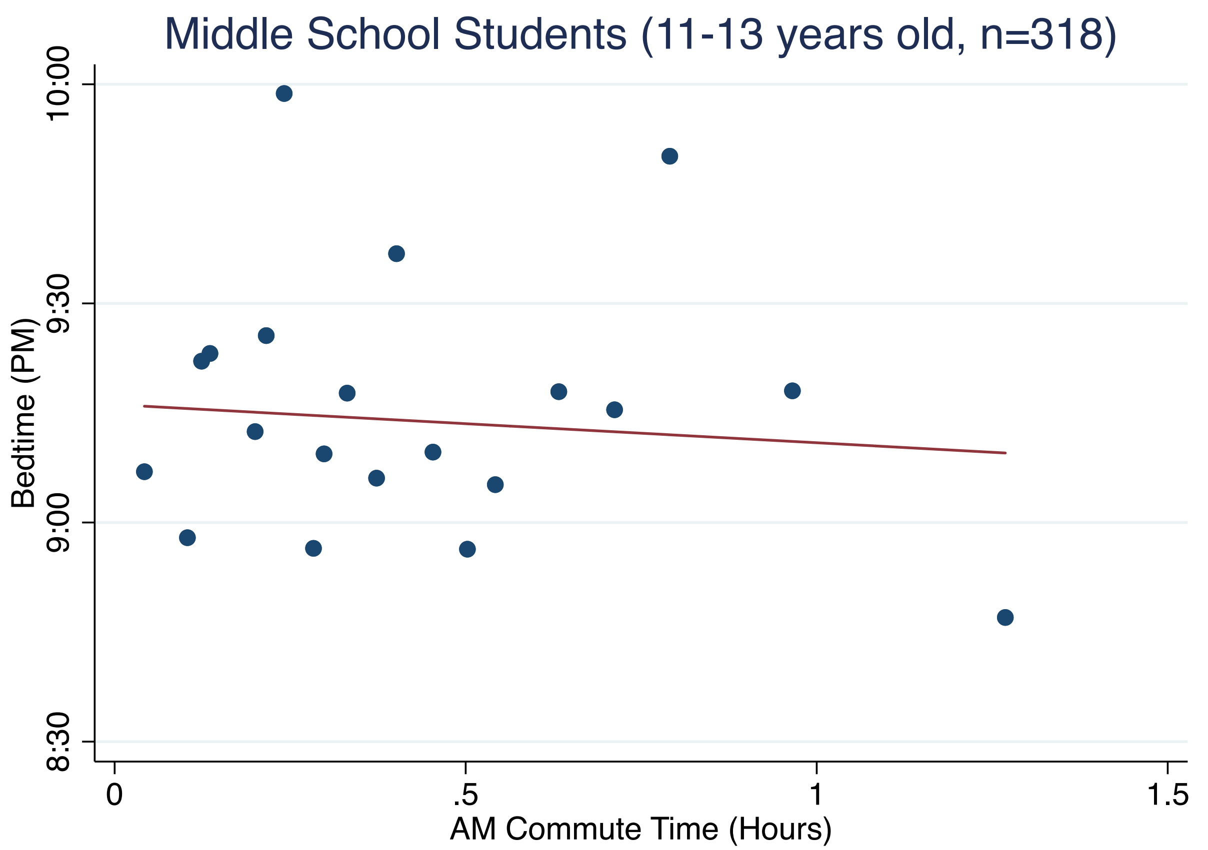
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A18: Morning Commute Time versus Sleep – Middle School Students



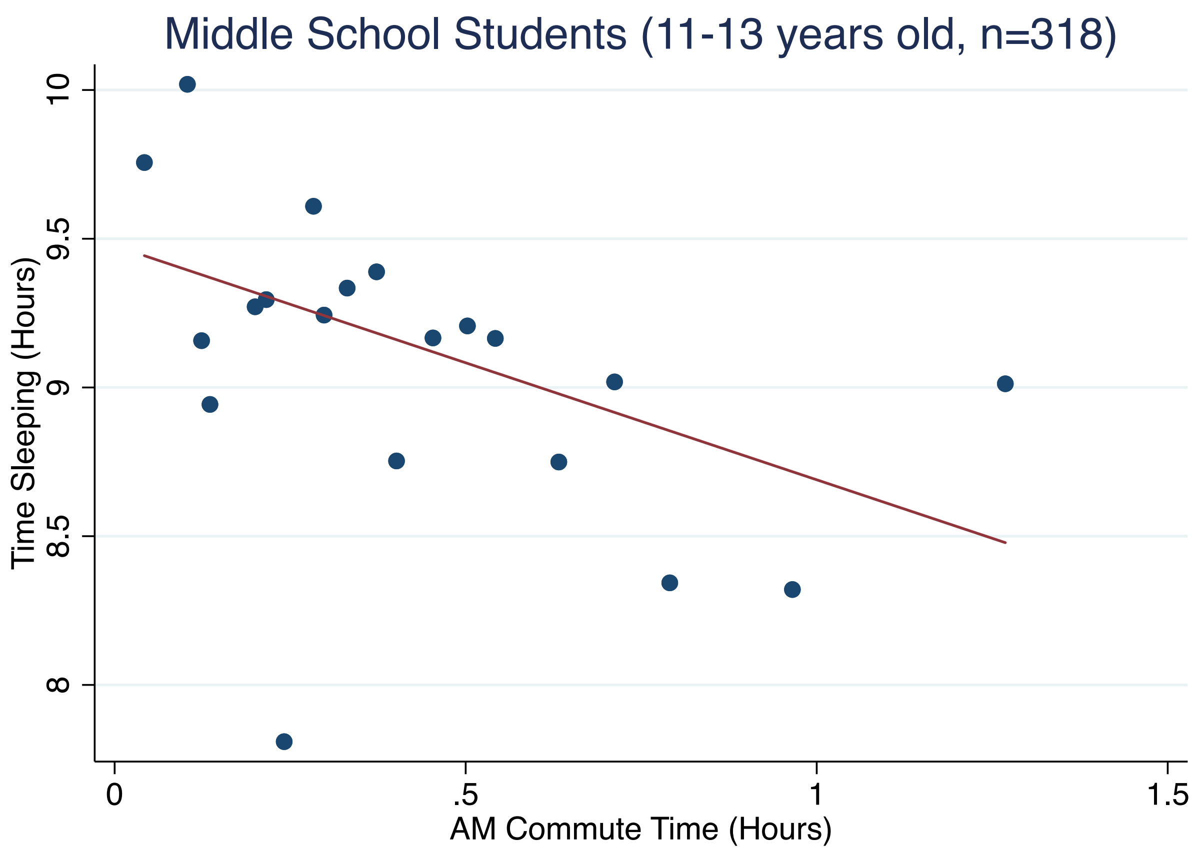
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A19: Morning Commute Time versus Sleep – Middle School Students



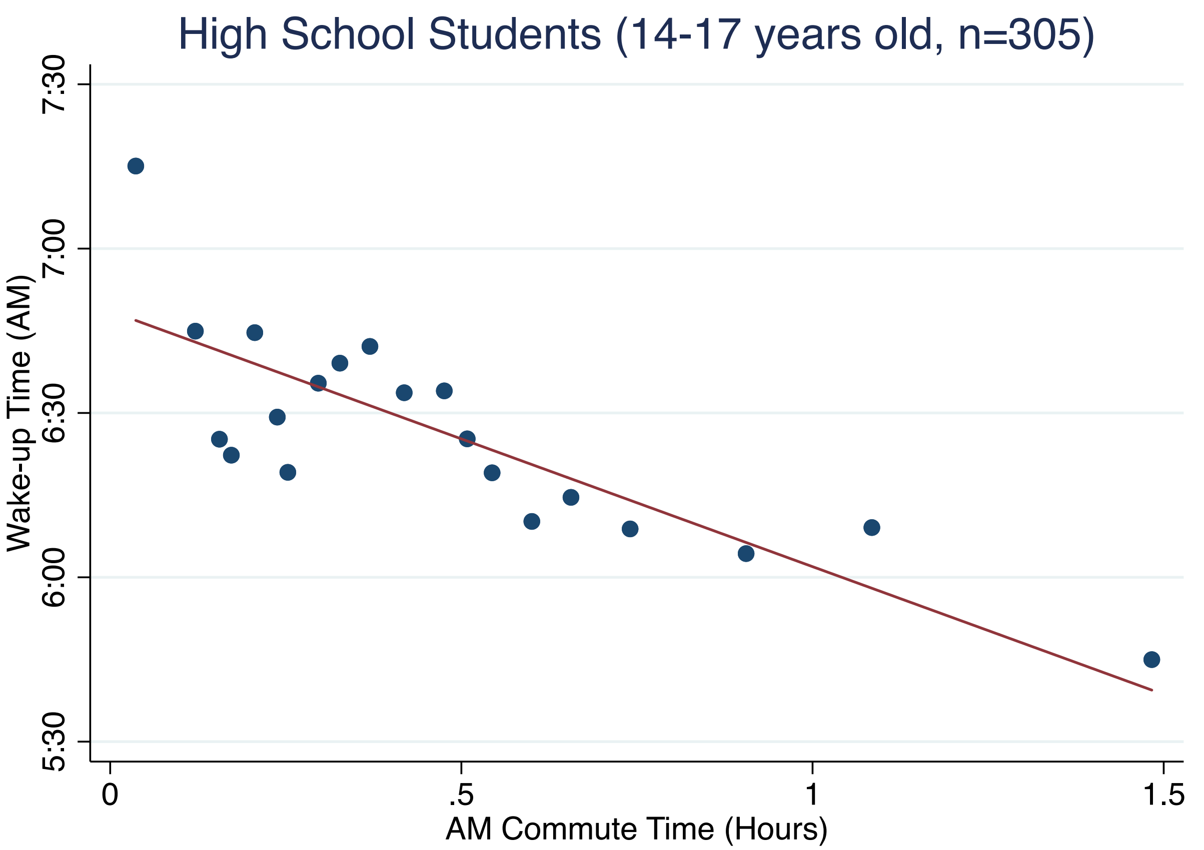
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A20: Morning Commute Time versus Sleep – Middle School Students



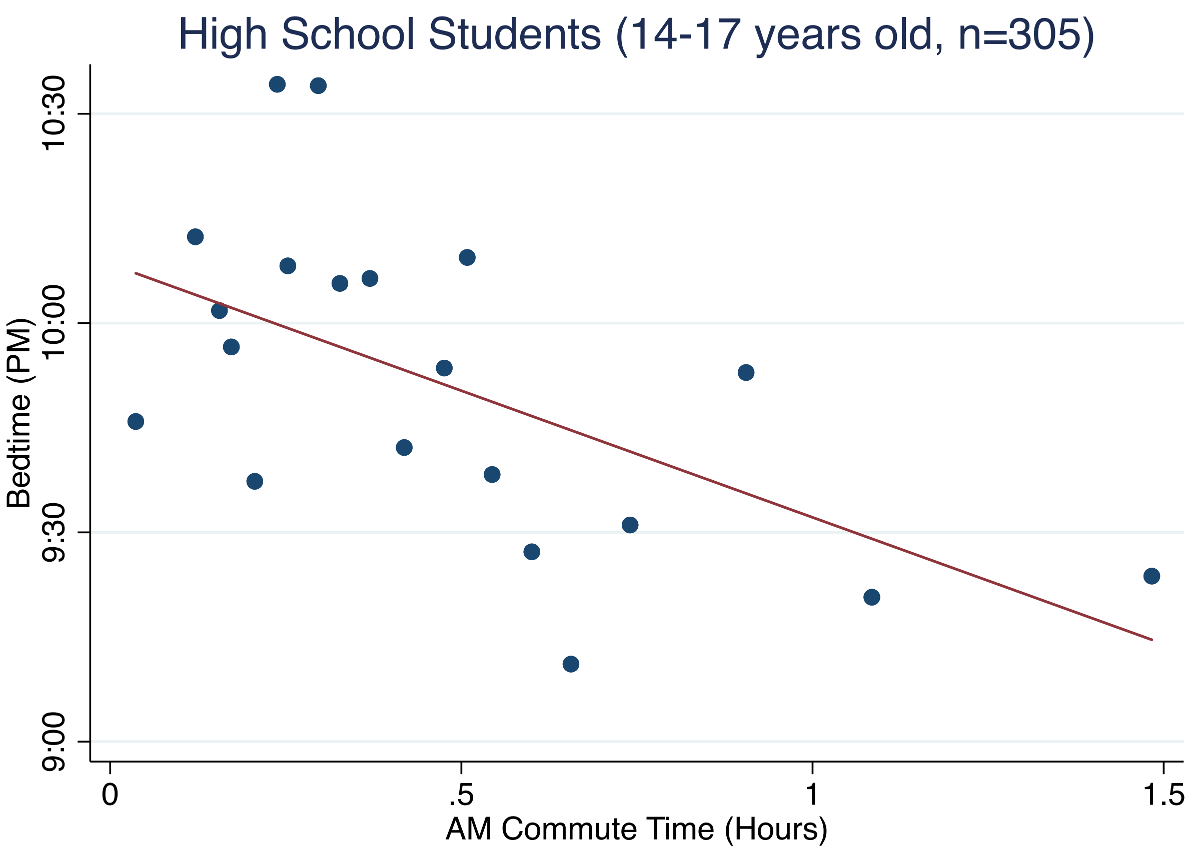
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A21: Morning Commute Time versus Sleep – High School Students



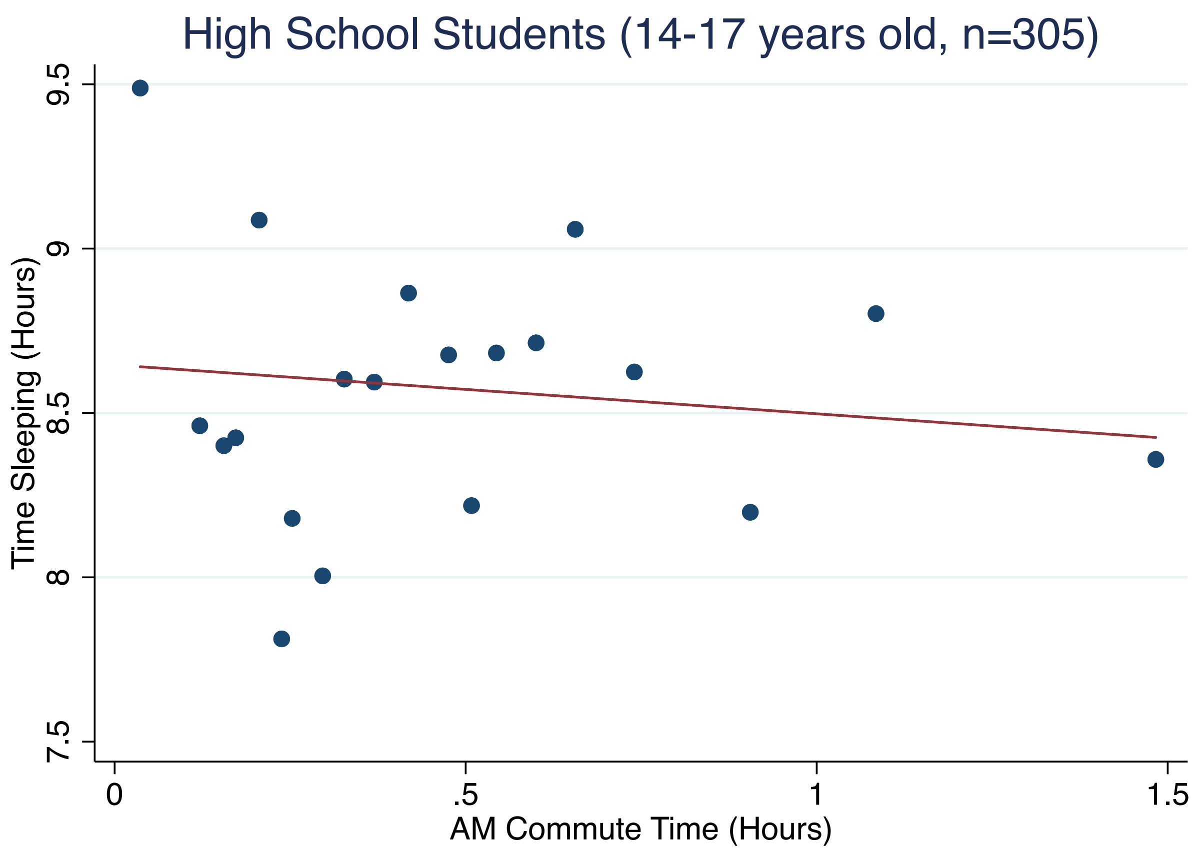
Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Figure A22: Morning Commute Time versus Sleep – High School Students



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 A23: Morning Commute Time versus Sleep – High School Students

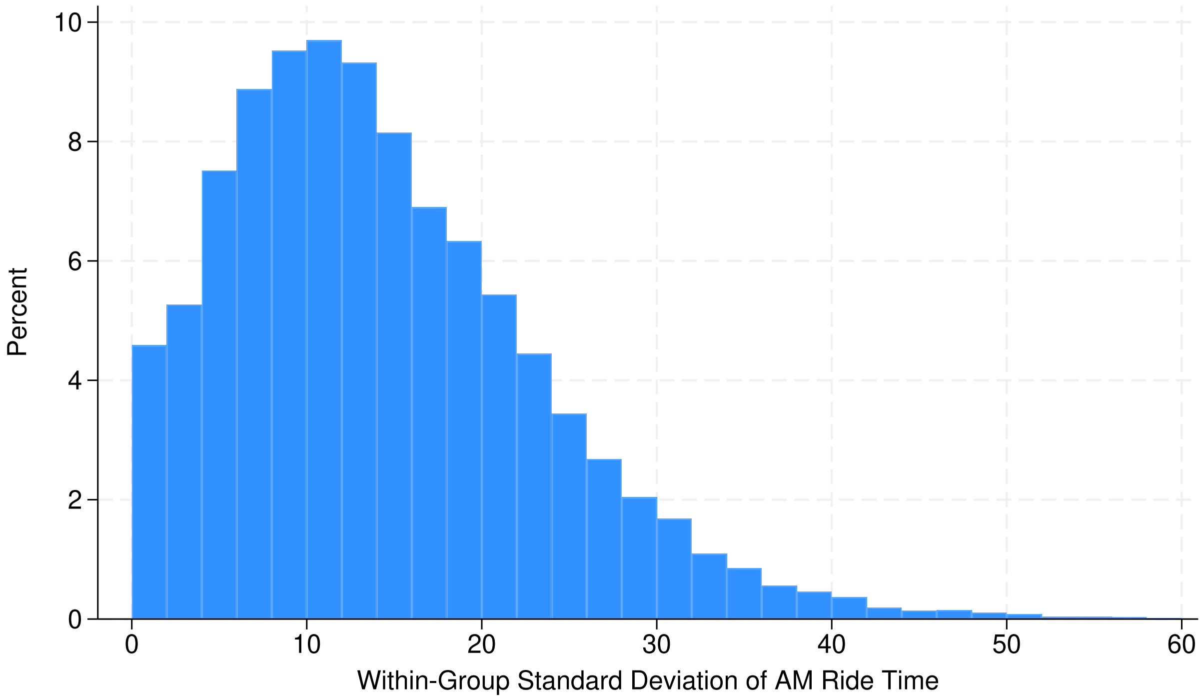


Binned scatter plots show morning commuting time versus wake-up time, time sleep begins, and total time sleeping over a 24-hour period from the 2014 and 2019 PSID-CDS conditional sex, and family income. The sample includes one observation per student and is restricted to observations that occur on Monday-Thursday.

Appendix B Variation within Comparison Groups

B.1 Bus Route Fixed Effects

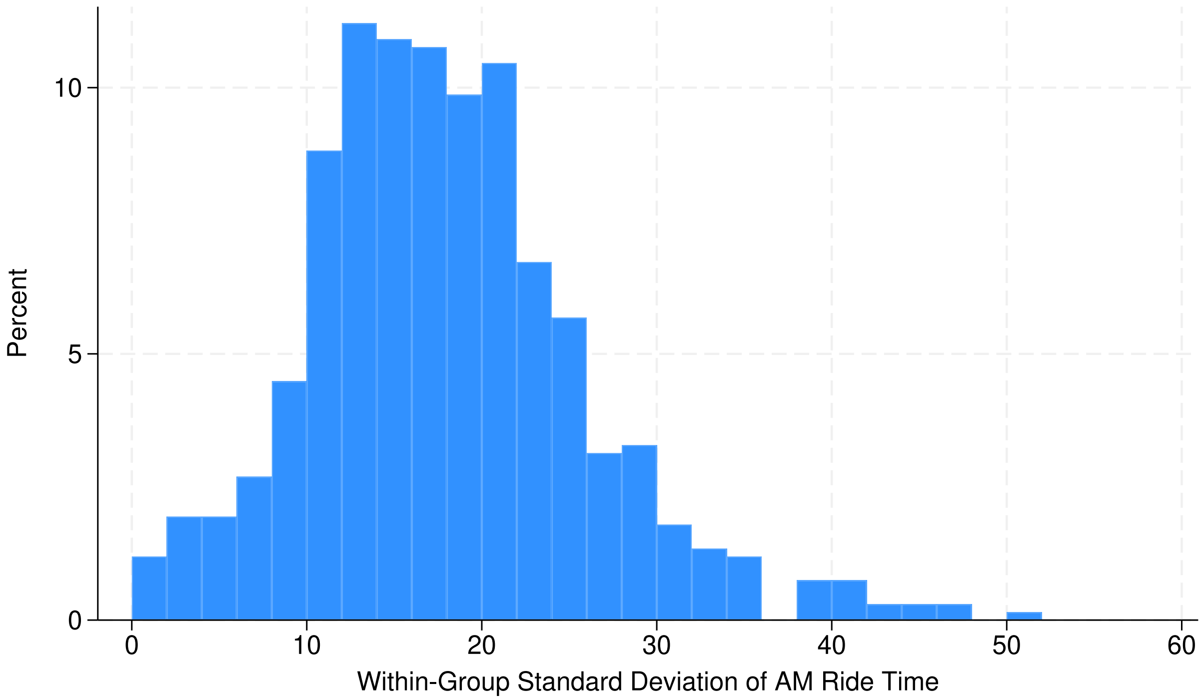
Figure B1: Variation within Bus Route



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

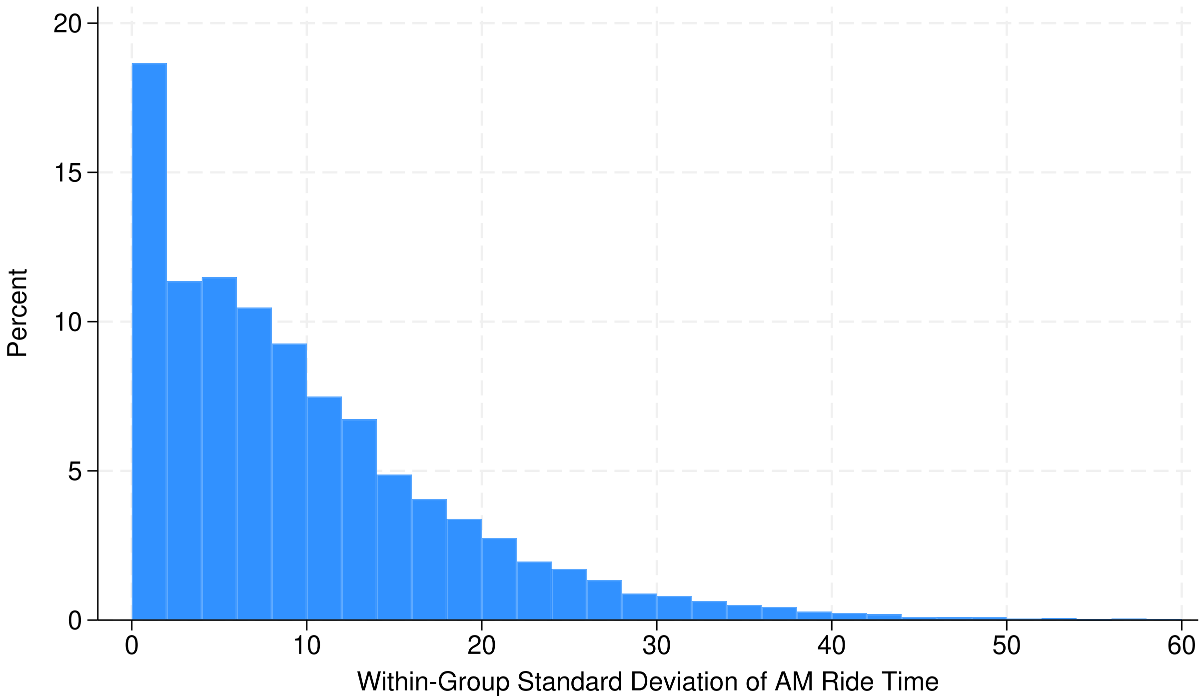
Figure B2: Variation within Distance Ring



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

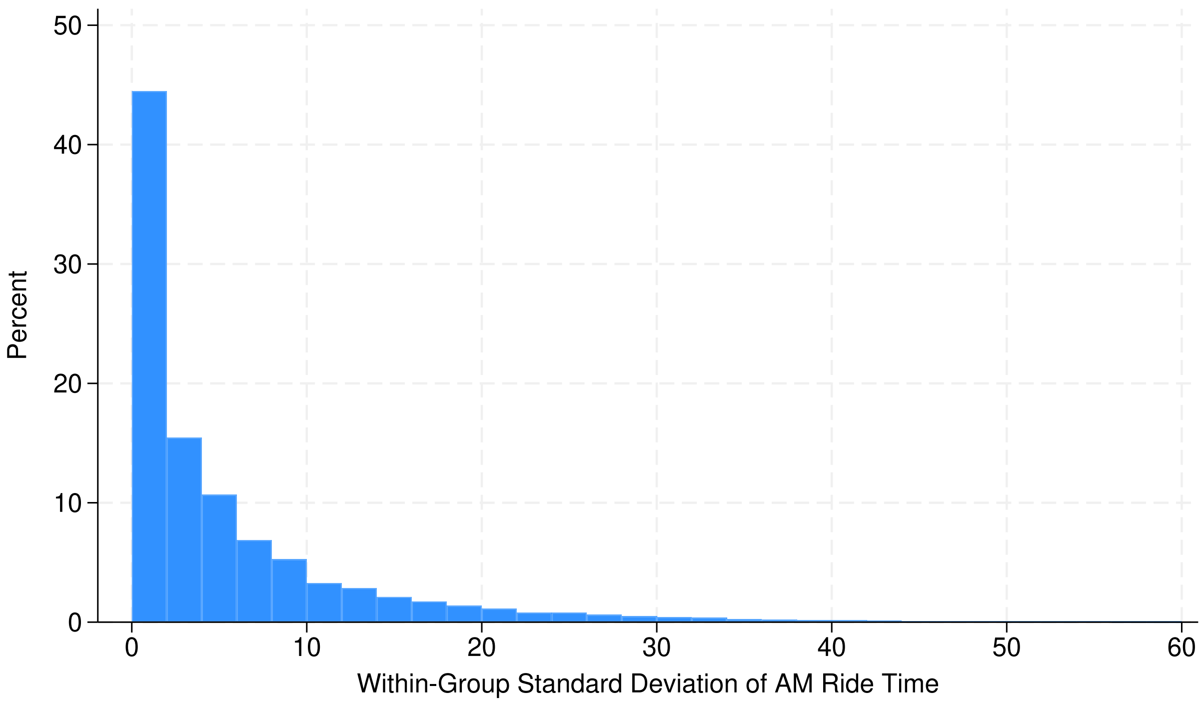
Figure B3: Variation within Distance Ring × Bus Route



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.