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Abstract

We study the effects of informal social interactions on academic achievement and behaviour using idiosyncratic variation in peer groups stemming from changes in bus routes across elementary, middle, and high school. Our results suggest that student interactions outside the classroom—especially in adolescence—may be an important factor in the education production function for both academic and, particularly, behavioral skills. The effects of interactions on the bus are also related to neighborhood measures—suggesting that one way that interactions on the bus may matter is by amplifying interactions in the neighborhood.

JEL-Codes: I210, C310.

Keywords: social interactions, peer effects, education, behavior.

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1 Introduction

Recent work has documented the importance of neighborhood context for educational and labor market outcomes (Chetty et al., 2016; Chetty and Hendren, 2018). While some results suggest that peers play a central role in explaining neighborhood effects (Deutscher, 2020), researchers across the social sciences still seek to understand how and why place matters. Coming from a different direction, a separate body of work in the context of education provides empirical evidence for the existence of peer effects occurring largely in classroom settings.[1] For example, Carrell and Hoekstra (2010) find that disruptive school-peers can negatively affect an individual student's academic achievement and behavior and follow-up work finds that these effects can extend to downstream labor market outcomes (Carrell et al., 2018).

Still, since only a fraction of the time students spend outside their homes occurs in the classroom and classroom-based interactions take place in highly mediated environments distinct from granular neighborhood geographies, peer effects in structured environments like the classroom are unlikely to explain much of the causal effects of place. Instead, repeated and informal social interactions among smaller groups of students—whether in the cafeteria, during recess, or on the school bus—are likely to better resemble the types of interactions that take place in settings like neighborhoods.

In this paper, we study the role of repeated informal social interactions on human capital development and introduce a novel approach to estimate the effects of social interactions that can be extended to additional settings. Focusing on interactions among same-grade peers who share a bus route, we seek to bridge neighborhood and school contexts and shed light on an understudied component of the education production function which often constitutes a period of time equivalent to roughly a class period. Moreover, we aim to shed light on whether these types of informal social interactions affect academic versus behavioral outcomes, and at what age these types of interactions are likely to be most meaningful.

We consider a model of social interactions where the ways in which students influence each other depends on the particular set of peers surrounding them, and where peer culture can influence students in different ways (e.g., academics vs. behavior). Our object of interest is how a particular grouping of individuals causes its constituent members to perform differently than they might in other contexts.

One empirical challenge in identifying the effects of social interactions is that they are not exogenously determined. This is particularly true in our context—the school bus—since families choose neighborhoods based on their resources and preferences, and the decision whether or not a child rides the bus is likely a function of school district policies and a family's choice of geography that is conditional on many factors. Another challenge to identifying peer effects is that they can

[1] See Durlauf and Ioannides, 2010 or Sacerdote, 2011 for overviews.

take place in a number of ways and can be difficult to observe.

By focusing on idiosyncratic changes to the sets of students riding the bus together that result from school transitions and the spatial structure of bus routes, we develop an approach to estimating peer effects that takes advantage of transition data. Recognizing the importance of taking into account the unobservable parts of peer interactions, we estimate peer effects by measuring the extent to which changes in the unexplained component of the performance of a student's bus peers predicts otherwise unexplained changes in that student's own performance. Our strategy builds on recent work extending value-added estimation to new settings including teamwork, guidance counselors, and schools (Weidmann and Deming, 2021; Isphording and Zölitz, 2020; Mulhern, 2023; Jackson et al., 2020).[2] However, rather than focusing on how an individual shifts group behavior, we focus on how the group affects its constituents' behavior. We estimate our model using a leave-out-student (jackknife) strategy where we estimate the effects of bus peers for each student leveraging data only from their peers. Our identifying assumption is that shifts in bus-peers resulting from changes in the geography of bus routes at school transitions are uncorrelated with other changes specific to those sets of bus-peers—but unrelated to their bus route, or the relationships developed on the bus route.

To estimate our model, we use administrative data from North Carolina's largest school system where a majority of students rides the bus to and from school. On average, the informal social interactions we study take place among roughly a dozen students, and last for slightly more than a half hour each day. To provide us with insight into the role of informal peer interactions in both childhood and adolescence, we estimate the effects of social interactions on the bus using students transitioning from both elementary to middle school and middle to high school.

Estimates from our elementary and middle school sample show that a one standard deviation shift in bus peers corresponds to changes in academic achievement of 0.03 standard deviations (SD) and behavior of nearly 0.05 SD. In contrast, we find substantially higher estimates in our middle and high school sample, where a one standard deviation shift in bus peers corresponds to a nearly 0.05 SD increase in academic performance and a 0.08 SD improvement in behavior. Together, these results suggest that out-of-classroom interactions may be more meaningful in adolescence than in childhood. Interestingly, bus peers appear to have distinct effects on academics and behavior—with potentially larger effects on behavior than academics. While our estimates in early grades are small, comparisons to other variance-based estimates of the education production function suggest that the effects in middle and high school are of a similar magnitude to those documented in research on the value of peers in business school (Isphording and Zölitz, 2020), about half the magnitude of school effects (Jackson et al., 2020), half the magnitude of the effects of school counselors (Mulhern, 2023), and less than half the magnitude of teacher effects (Chetty et al., 2014; Jackson, 2018; Kraft, 2019).

[2] See also earlier work by Bramoullé et al. (2009) and De Giorgi et al. (2010) on using the repeated randomization of students to groups to estimate peer effects outside of the value-added framework.

To better understand how social interactions on the bus might affect academic performance and behavior, we conduct several empirical exercises. Most notably, we link our sample to data from Chetty et al. (2018, 2022) and a detailed survey conducted in our site district to study the extent to which bus effects are correlated with neighborhood, bus, and school characteristics. These results highlight a handful of noteworthy points. First, the effects of social interactions on the school bus are only partly related to students' prior academic performance. Second, we find little evidence that these bus effects are related to survey-based measures of school climate or student engagement. Instead, neighborhood contexts appear salient for social interactions on the school bus through all grades, suggesting that one way that interactions on the bus may matter is by amplifying interactions in the neighborhood after school. Although we find that students from minority backgrounds are least likely to benefit from informal social interactions on the school bus, our results do not support the idea of homophily in social interactions by race and gender (Hoxby, 2000; Currarini et al., 2009; Bennett and Bergman, 2021). In interpreting these results, it is important to note that we do not have actual data on the nature of informal social interactions or the duration peers spend with each other. Still, bus routes provide conditionally exogenous variation in the composition of individuals whom students meet regularly. Moreover, these regular meetings on the school bus could result in more meaningful interactions not just in informal settings—such as those that occur before or after the school day—but also in the classroom.

Our work extends recent papers by Weidmann and Deming (2021) and Isphording and Zölitz (2020) who develop an innovative experimental approach to estimating peer effects in the context of teamwork. We show that a similar approach can be applied to study the effects of peer groups on individuals (rather than individuals on individuals or individuals on groups) within the context of unstructured settings where informal social interactions prevail.[3] Where their approaches assume that an individual's effect on the group is constant across different settings or sets of peers (i.e., that the causal effect of a group is the additively separable sum of the constant effects that each peer has on others), our approach relaxes this assumption by allowing the effect that an individual has on others to depend on the particular set of people around them.[4] Moreover, we show that this

[3]These types of situations are likely to be common. For example, when placed together, a group of competitive students may work to outshine each another academically—raising the performance of the entire group; instead, when a competitive student is placed with students explicitly not interested in competition, the new situation may engender a dynamic where there is tension among the students, potentially leading to behavioral problems.

[4]These models are not at odds with each other, but capture different parts of social interactions. The peer effects identified by Isphording and Zölitz (2020) and Weidmann and Deming (2021) represent the part of peer effects that is additively separable across the individuals who make up a group. Instead, our model captures the aggregate peer effect. Insomuch as this is the case, we sidestep the issue of causal arrows between individuals. For example, a leader might shift student behavior in a particular direction—but this group leader can only lead if they are exposed to a set of students willing to be led. In this sense, asserting that the leader "caused" others to shift their behavior in a particular direction is not quite accurate—the fact is that the leader and those who met in that context contributed to that particular group dynamic.

set of approaches for estimating peer effects can be extended to observational settings that involve transitions between peer groups—an identification strategy that is potentially applicable across a wide array of settings involving shifting group composition and teams—whether in education, work, or play (e.g., team sports).

Substantively, our results support the idea that social interactions in informal settings outside of school can have ramifications for what occurs within the classroom. Agenda-setting work by Chetty et al. (2016) establishes the significance of a child's neighborhood as a determinant of labor market outcomes. While the mechanisms by which these effects are transmitted remain largely unknown, new work has begun to extend these findings, and suggests that peers—especially in adolescence—may play a role (Deutscher, 2020; Agostinelli et al., 2020). Linking neighborhoods and education, prior work suggests that neighbors might have little effect on academic performance but can influence behavior and patterns of higher educational choice (Gibbons et al., 2013, 2017; Barrios Fernández, 2022).[5] We provide evidence on how a particular type of social interaction outside the classroom can affect academic and behavioral outcomes in distinct ways. By providing estimates at different grade levels, our results corroborate the results from the neighborhood effects literature, suggesting that peers may be particularly influential during adolescence. Our results also suggest that disadvantaged groups are least likely to benefit from social interactions on the school bus, highlighting the importance of additional research that examines the role of informal settings in perpetuating socioeconomic disadvantage.

Further, our results extend to a sparse literature describing factors that can shape behavioral skills. As recent work has documented the growing importance of social skills in the labor market (Deming, 2017; Jokela et al., 2017; Edin et al., 2022; Barrera-Osorio et al., 2023), understanding how to develop these types of skills is increasingly vital. Empirical work suggests that early childhood education may lead to improved social skills (Deming, 2009; Heckman et al., 2013). More recent work finds that teachers can affect behavioral skills—even in adolescence (Kraft, 2019; Jackson, 2018). Our work contributes to this literature by demonstrating that social interactions also affect behavior, and reaffirming that behavior may be malleable beyond childhood.

[5]Interactions outside the classroom have also been studied higher education (Sacerdote, 2001; Zimmerman, 2003; Marmaros and Sacerdote, 2006; Camargo et al., 2010; Garlick, 2018; Corno et al., 2022; Michelman et al., 2022) and in a handful of other settings such as sports (Mousa, 2020; Lowe, 2021). In contrast to the context in our paper, these studies often focus on either an extremely intense form of interactions (college roommates) or academically oriented interactions (study groups).

2 Setting and Data

2.1 School buses

The trade-off between empirical settings and data typically hinder the analytical study of informal social interactions. Where data are rich, settings are limited. For example, the relatively large literature that examines peer effects typically uses classrooms as settings and leverages detailed administrative data to examine social interactions. While time in classrooms represents a substantial portion of a student's waking hours and exposure to peers, there exist many other settings where data are qualitative in nature or simply unavailable. These settings include neighborhoods, the cafeteria, extracurricular groups, and sports teams. We use administrative data from the school bus setting in order to measure the extent to which informal social interactions shape later outcomes.

The school bus represents an important social setting for two primary reasons. First, the time students spend on a school bus is largely unstructured. Students are typically free to choose their seats and their peer groups. While bus drivers—usually the only adult on the bus—may exercise discretion by assigning seats or moderating behavior, their influence over broad types of student interactions is likely a fraction of that exercised by either parents or classroom teachers and, as prior research suggests, is likely to be limited (Brown et al., 2021).

Second, school bus ridership is widespread and constitutes a meaningful portion of a student's day. More than half of the roughly 50 million American public school students ride the bus, a rate that peaked at 60% throughout the 1980s and has hovered around 55% in the years since (Blagg et al., 2018). While data on school travel time is limited, recent work from the Urban Institute shows that time on public transportation, which includes school buses, lasts roughly as long as a single class period for middle and high school students. In large U.S. public school systems in Denver, Detroit, New Orleans, New York City, and Washington DC, the median round-trip ride time was 40-62 minutes (Blagg et al., 2018)—comparable to the duration of a typical class period. Unlike classrooms, however, which are structured to optimize formal cognitive and interpersonal development, school buses are informally organized by virtue of students' social preferences and facilitate the development of complementary sets of social skills.

2.2 Institutional setting, data sources, and outcomes

We examine the influence of informal social interactions on student outcomes in a large, representative school system with substantial student ridership. The Wake County Public School System (hereafter, Wake County) is the largest school district in North Carolina and the 15th largest in the U.S. (De Brey et al., 2023). The district has roughly 170,000 students enrolled in 180 schools, and is known for its socioeconomic school integration program (Parcel and Taylor, 2015; Carlson et al., 2020), magnet schools (Dur et al., 2023), and year-round schools (McMullen and Rouse, 2012). Wake County mirrors the U.S. education landscape across a number of indicators. Perhaps most importantly for this study, a comparable but slightly higher proportion of students compared to the U.S. average rides the bus to school—roughly 60 percent. The average Wake County rider spends about 37 minutes on round-trip bus travel and travels about 4.5 miles.[6] Since exposure on the bus might lead to friendships both in school and at home, the time that students spend on a bus together should be seen as the lower-bound of the collective time that these students spend together.

Our sample draws from Wake County administrative data across four academic years (2015-16 to 2018-19) and is described in Table 1. Given that our empirical strategy requires us to compare students as they transition from either elementary to middle school (ES-MS Sample) or from middle to high school (MS-HS Sample), we include students enrolled in grades three to eight in the fall of 2015 in our full sample (See Appendix Table A.1). This full set of students is described in Column 1 of Table 1.

Since our model will require multiple time periods of exposure among each set of peers, we focus on students who share the same grade and ride the bus together for multiple years. We describe school bus assignment in Appendix Section A and detail how our data are constructed. On average, each student in our estimation sample has about 12 same-grade students meeting our sample requirements on the bus. (See Appendix Figure A.1 for total bus rider distribution and Appendix Figures A.2-A.3 for same-grade bus ridership distributions.) So that we base our estimates off of changes in same-grade bus-peers that occur at school transitions, we define the peer groups that ride the bus together based on each student's bus in the last year of elementary(/middle) school and the first year of middle(/high) school. As such, we observe each student in exactly two of these sets. This prevents any changes in bus ridership within schools that is not associated with school switching. Yet, since some students do change their bus during elementary school period, our subsequent estimates should be interpreted as intent-to-treat (ITT) effects. While we do not aim to construct a cardinal ranking of bus effects, and thereby do not need our bus groups to belong to a single connected set, we require that the set of students an individual is exposed to on the bus changes with school transitions and therefor exclude bus-groups which are unconnected to at least some other bus-groups at schools transitions. Together, each estimation sample includes nearly 4,000 sets of same-grade bus-peers.

Our primary outcomes are academic achievement and behavior, constructed as follows. We create an index for academic achievement based on performance on state standardized test scores in math and reading in elementary and middle school and grade point average (GPA) in high school. We give these components equal weight, and standardize our measure of academic performance to have a mean of zero and unit standard deviation for each year and grade. We create a behavioral

[6]See Appendix Figure A.4 for more details on the district's transportation policy.

index using factor analysis, relying on measures of absences, tardies, and short-term suspensions. This index reflects recent research suggesting that administrative data on attendance and discipline can provide useful information on student behavior (Jackson, 2018), as well as work suggesting that students influence each other's attendance and disciplinary behavior in meaningful ways (Bennett and Bergman, 2021). Our behavioral index is standardized similarly to the academic index. Riders and non-riders are more or less comparable on academic and behavioral measures. We present correlations across all outcomes in Appendix Tables A.2-A.4. The construction of other variables is described in detail in Appendix Section A.

In columns two and three of Table 1, we report how students who ride the bus compare to students who do not ride the bus. On average, a student who rides the bus spends more than fifteen minutes traveling in each direction, totaling roughly 37 minutes. There is, however, considerable variation (SD = 27 minutes) in the duration of time students spend on the bus. Asian, Black, and Hispanic students are each more likely to ride the bus than not, while white students are significantly less likely to ride the bus to school. Students who ride the bus tend to perform slightly lower (0.04-0.07 SD) than students who do not. Riders and non-riders are more comparable across behavioral dimensions.

In the two rightmost columns (4 and 5), we create two separate samples for use in our analyses. The ES-MS sample consists of students who began grades 3-5 in the fall of 2015 and the MS-HS sample consists of students who began grades 6-8 that same fall. Due to the requirements of our estimation strategy, we restrict these samples to students who ride the bus to and from both elementary(/middle) and middle(/high) schools. We also exclude students who do not share the bus with any other students in their own grade and students who are retained, since it is not altogether clear which cohort these students would be assigned to. This leaves us with roughly 12,000 students in our ES-MS sample and 13,000 students in the MS-HS sample. We follow these students for up to four years.

Table 1: Descriptives

	Full sample (1)	Riders (2)	Non-riders (3)	ES-MS Sample (4)	MS-HS Sample (5)
			Panel A: Student Characteristics		
Male	0.49	0.50	0.48	0.50	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Asian	0.09	0.10	0.09	0.11	0.09
	(0.29)	(0.30)	(0.28)	(0.31)	(0.29)
Black	0.21	0.24	0.18	0.22	0.24
	(0.41)	(0.42)	(0.38)	(0.41)	(0.43)
Hispanic	0.17	0.21	0.13	0.25	0.19
	(0.38)	(0.40)	(0.34)	(0.43)	(0.40)
White	0.48	0.42	0.56	0.39	0.43
	(0.50)	(0.49)	(0.50)	(0.49)	(0.49)
Other race	0.04	0.04	0.04	0.04	0.05
	(0.20)	(0.20)	(0.20)	(0.19)	(0.21)
English language learners	0.05	0.06	0.04	0.06	0.04
	(0.22)	(0.24)	(0.19)	(0.24)	(0.20)
			Panel B: Achievement		
Math achievement	-0.00	-0.04	0.06	-0.05	-0.07
	(1.00)	(1.01)	(0.98)	(1.02)	(1.02)
Reading achievement	-0.00	-0.07	0.10	-0.05	-0.08
	(1.00)	(1.02)	(0.97)	(1.02)	(1.03)
Achievement index	0.00	-0.08	0.10	-0.03	-0.12
	(1.00)	(1.02)	(0.96)	(1.01)	(1.05)
Absences	7.20	7.61	6.68	6.46	7.10
	(8.37)	(8.70)	(7.90)	(6.80)	(9.33)
Tardies	4.87	4.72	5.07	3.46	4.33
	(9.86)	(9.48)	(10.33)	(7.20)	(9.16)
Short-term suspensions	0.03	0.04	0.02	0.04	0.05
	(0.25)	(0.28)	(0.21)	(0.28)	(0.34)
Behavior index	0.00	-0.02	0.03	0.04	0.04
	(1.00)	(0.99)	(1.01)	(1.00)	(1.04)
			Panel C: Bus Characteristics		
Bus ride duration (minutes)				36.42	37.91
				(26.78)	(26.71)
Same-grade bus-peers				12.29	12.65
				(5.50)	(5.62)
Observations	266,550	149,780	116,770	47,457	51,045
Students	82,705	41,535	41,170	12,342	13,247
Sets of same-grade bus-peers				3,848	3,758
Schools	189	186	187	134	62

Notes: Means and standard deviations are reported for background characteristics and outcomes for our full sample, bus-riders, non-riders, as well as our two estimation samples separately. The full sample consists of student-by-grade-by-year combinations that comprise each of three cohorts we follow (See Appendix Table A.1).

3 Empirical strategy

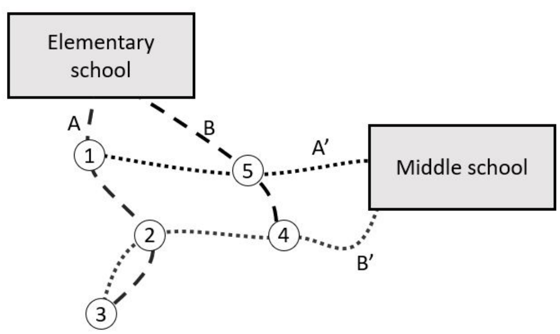
The aim of this paper is to study the role of informal social interactions on the development of academic and behavioral skills at different developmental stages. For a clarification of the conceptual framework underlying our empirical approach, see Appendix B.

The central empirical challenge comes from separating the bus effect from other factors correlated with which bus a student rides. For example, children from affluent or poor families are likely to cluster together on buses—making it difficult to separate systematic differences in achievement stemming from social interactions on buses from those rooted in family resources or preferences.

To isolate the extent to which peers on the school bus contribute to a student's outcomes, we focus on variation in bus-peers associated with transitions between elementary and middle schools or middle and high schools, holding individual, grade, school, and year effects fixed. This remaining variation in peer groups stems from the idiosyncratic spatial structure of bus routes. Observing each student in more than one group allows us to estimate individual effects, independent of any specific group; and, observing large numbers of students in each set of schools and grades allows us to estimate school and grade effects.[7]

For example, consider the bus routes depicted in Figure 1. Two set of students, A:{1, 2, 3} and B:{4, 5}, ride the bus to elementary school, while the same students ride the bus to middle school in sets A':{1, 5} and B':{2, 3, 4}. Our analytic strategy examines shifts in academic performance and behavior common to bus-peers which occur at school transitions.

Figure 1: Analytic strategy



Notes: Figure 1 represents bus routes {A, B, A', B'} to elementary and middle school for five students, each living in a distinct neighborhood. Students {1, 2, 3} and {4, 5} ride the bus together to elementary school, while students {2, 3, 4} and {1, 5} ride the bus together to middle school.

Identification fails if changes in the peer group riding a bus coincides with other time-varying

[7]Durlauf and Ioannides (2010) suggest that "the use of transition versus steady-state data to infer social interaction effects should attract attention."

issues that affect student performance. Perhaps the most serious challenge to our strategy occurs if a student's family moves within Wake County the same year they would transition from elementary to middle school (or from middle to high school). This is not an unrealistic scenario: families do move in search of better schools for their children, and these moves can coincide with school changes. To shield our estimates from this type of threat, we include a school-by-school-pair fixed effect in our estimating equations to absorb variation in outcomes associated with family preferences for schools that deviate from the typical school transition.[8]

Formally, we extend variance-based approaches to identifying peer effects (Glaeser et al., 1996; Graham, 2008) using techniques from the teacher value-added and firm-worker match literatures (e.g., Abowd et al., 2008; Kane and Staiger, 2008; Chetty et al., 2014; Jackson, 2018), and focus on exogenous variation stemming from changes in bus routes. But notably, by focusing exclusively on shifts in peer sets occurring at school transitions, we avoid some of the potential issues related to non-random mobility between firms in the firm-worker match literature (Card et al., 2018).

As students may influence academic performance and behavior in different ways, our main outcomes are indices (Y_{ibsgt}) of academic and behavioral outcomes for all students each year, described in Section 2.

We decompose variation in student outcomes over time across various dimensions: bus (b), individual (i), school-by-school-pair (s), grade (g), and year (t). Instead of simply including a school fixed-effect, we include school-by-school-pair fixed-effects to make sure that atypical changes in school attendance do not drive our main estimates.

$$Y_{ibsgt} = \alpha_i + \mu_b + \phi_s + \gamma_g + \delta_t + \epsilon_{ibsgt} \tag{1}$$

To ensure that there is no mechanical relationship between the bus effect and a student's own outcomes, we use a jackknife approach, where each student's bus effect is estimated from the common component across other students on their bus.[9] To do this, we estimate each student's bus effect from the above regression, where that particular student is left out of the estimation sample:

$$\tilde{\mu}_b^i = \hat{\mu}_b^{-i} \tag{2}$$

To isolate the extent to which peers on the school bus contribute to a individual student's outcomes, we focus on variation in bus peers that stems from transitions between elementary and middle schools or middle and high schools. For example, as a student enters eighth grade and

[8]We assume that while a student's neighborhood and initial bus is not assigned at random, the change in bus peers between the first and second bus is as good as random. If this assumption is satisfied, we avoid the perils of spurious relationships in the correlations of residuals among peers (Angrist, 2014).

[9]This excludes any changes in a student's own outcomes that do not affect other students. As noted in the above section, our estimates include effects from both exogenous and endogenous interactions.

transitions from middle to high school, their bus will take a different route to school, and thereby contain a different set of students. If, for example, riding the bus together causes students to play together after school, this is something we want our model to measure. While we acknowledge that our estimates of bus effects contain elements beyond social interactions between peers—for example, students may be affected by common shocks stemming from a strict bus driver or poor ventilation—we believe the potential magnitude of the effect of these sources to be relatively minor. Moreover, they should be included in any broader estimate of bus effects, particularly if we think that groups of people can behave differently in different contexts.

While the estimates of bus effects recovered by our jackknife estimates, $\tilde{\mu}_b$, are unbiased measures of the effects of bus b on outcome Y, we shrink them by their reliability to minimize mean squared prediction error since these are estimated with noise (Kane and Staiger, 2008; Chetty et al., 2014).[10] To do this, we follow a set of recent papers that directly estimate similar variances in different contexts using a model-based approach (Jackson, 2018; Kraft, 2019; Mulhern, 2023). We estimate the variance components by fitting the following mixed-effects model, where we adapt Equation 1 to include bus random effects (μ_b is estimated as a random rather than fixed effect):

$$Y_{ibsgt} = \alpha_i + \mu_b + \phi_s + \gamma_g + \delta_t + \epsilon_{ibsgt} \tag{3}$$

$$\mu_b \sim N(0, \psi); \epsilon_{ibsgt} \sim N(0, \theta)$$

Since the reliability of our estimates of bus effects depends on the number of years that we observe the set of students on the bus together n_b, we calculate the reliabilities of each bus effect as shown, where the terms $\hat{\sigma}_\mu^2$ and $\hat{\sigma}_\epsilon^2$ are estimated directly from the mixed model in Equation 3:

$$\lambda_b = \frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\mu^2 + \frac{\hat{\sigma}_\epsilon^2}{n_b}}. \tag{4}$$

We then use an empirical Bayes approach to shrink our jackknife estimates by multiplying them by their reliabilities (λ):

$$\tilde{\mu}_b^i = \hat{\mu}_b^{-i} \lambda_b \tag{5}$$

Finally, so that we interpret the magnitudes of bus effects in terms of standard deviations as is commonly done in the literature on teachers (see, for example, Chetty et al., 2014), we standardize these values to have a mean of zero and unit standard deviation.

[10] While it is possible that our estimates are attenuated by exclusion bias—the mechanical negative relationship between an individual's outcome and the leave-out-mean of that outcome (Guryan et al., 2009; Angrist, 2014; Fafchamps and Caeyers, 2020)—our empirical Bayes procedure should help to mitigate some of this bias.

We follow this process for both our elementary and middle school sample and the middle and high school sample.

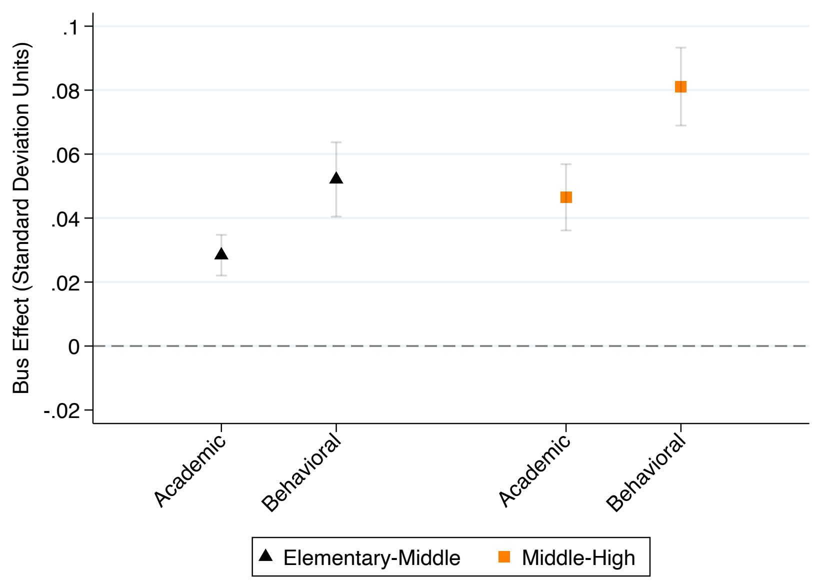
4 Results

4.1 Main results

After recovering estimates of bus effects in academic and behavioral dimensions for both the elementary and middle school as well as middle and high school samples, we assess the magnitudes of these relationships using regressions of the form described by Equation 1. The coefficient β is identified from the relationship between the change in individual performance and the change in the leave-out-student bus-peer effects, $\tilde{\mu}$.

$$Y_{ibsgt} = \alpha_i + \beta \tilde{\mu}_b + \phi_s + \gamma_g + \delta_t + \epsilon_{ibsgt} \tag{6}$$

Figure 2: Effect of bus peers on academics and behavior



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects. All regressions include fixed effects for individual, school-by-school-pair, grade, and year. Standard errors are clustered at the bus-group level. For sample sizes from left to right, see Table A.5, Panel A, Columns (1) and (5) and Panel B, Columns (1) and (5).

Figure 2 illustrates our main results (these results are also presented in Appendix Table A.5). In our elementary and middle school sample we find that a one standard deviation shift in bus peers produces a 0.03 SD shift in a student's academic achievement and a 0.05 SD shift in their behavior. In our middle and high school sample we find that a one-standard deviation shift in bus peers results in a 0.05 SD and a 0.08 SD shift in academic achievement and behavior, respectively. To make sure that our effects are not driven by the empirical Bayes shrinkage, we also report our results without this step (Table A.6).

These results suggest two main takeaways. First, like other recent papers documenting that skills can be malleable in adolescence (Guryan et al., 2023), these interactions appear larger in the teenage years, which suggests that adolescent behavior is more malleable than foundational work on child development might suggest (National Research Council, 2000; Bonnie et al., 2019). Second, informal social interactions between students are likely to have greater effects on behavioral rather than academic outcomes.[11] While it is harder to meaningfully compare the magnitudes of effects across different outcomes, we also do see that compared to academic effects, the behavioral effects are larger as a share of the linear-in-means peer effects (Figure A.6).

To validate these results we follow an exercise from Card et al. (2018) and plot residuals in student outcomes—after accounting for student, school-by-school-pair, grade, and year fixed effects—for students who experience various magnitudes of shifts in their estimated bus effects in Appendix Figure A.5. So that we can observe at least two years of outcomes before and after the bus switch, we focus on the cohorts who we first observe in 4th and 7th grades in our ES-MS and MS-HS school samples, respectively. Reassuringly, these results generally show that the bus transition coincides with a change in residual performance, and that there is little evidence of trends in the residual before or after the bus transition.

Comparisons to other variance-based estimates of the education production function suggest that the effects in middle and high school are of a similar magnitude to those documented in research on the value of peers in business school (Isphording and Zölitz, 2020), about half the magnitude of school effects (Jackson et al., 2020), about half the magnitude of the effects of school counselors (Mulhern, 2023), and slightly less than half the magnitude of teacher effects on both academic and behavioral outcomes (Chetty et al., 2014; Jackson, 2018; Kraft, 2019).

To benchmark these estimates of interactions outside the classroom to those inside the classroom in the same estimation sample, we estimate how exposure to higher performing peers in the classroom affects academic achievement and behavior (Figure A.6). Like bus-peers, classroom peers have little effect on other students in elementary school, and much larger effects in middle and, especially, high school. While each set of estimates relies on distinct identifying assumptions and any comparisons of the magnitudes must be taken with a grain of salt, these results suggest that peers on the bus matter almost as much as classroom peers in terms of both academic performance and behavior. If anything, the relative magnitudes of the academic versus behavioral effects of bus versus classroom

[11] Prior work on peer effects also examines non-academic outcomes—see, for example, Gaviria and Raphael (2001).

peers suggest that peers on the school bus might matter relatively more for behavioral outcomes than classroom peers.

4.2 Mechanisms

We conduct several analyses to better understand how peer interactions on the school bus might affect academic achievement and behavior.

We begin by unpacking the main estimates. Table A.5 suggests that bus effects have distinct relationships to academic achievement and behavior. For example, the coefficient on the academic bus effect is considerably smaller when the outcome is the behavioral rather than the academic index. This result corresponds to the idea that peers who improve each others' academic performance might not improve behavior and vice versa. The one exception to this pattern is that, in middle and high school, bus effects on behavioral outcomes are associated with the academic performance of students who ride the bus together. When we examine specific measures that drive bus effects, we observe that effects on academic performance are driven primarily by math achievement rather than reading (Table A.7). The effects on behavioral measures are driven primarily by absences and tardies rather than short-term suspensions.

More substantially, we attempt to open the black box of peer effects and study how our estimates of bus effects are linked to neighborhoods, time on bus, and schools (Appendix Section F). To do this, we link our analytic sample to data from Chetty et al. (2018) and Chetty et al. (2022) and leverage rich survey data from our district site to correlate our estimates of both academic and behavioral bus effects with neighborhood, bus, and school characteristics. These analyses highlights several interesting patterns (Figures A.8 and A.9). First, across both of our samples we observe that academic bus effects are more strongly related to prior peer academic performance while behavioral bus effects are more strongly related to prior peer behavioral measures (see also Table A.10). Interestingly, we find more scope for the role of classroom peers in mediating the effects of bus peers in middle and high school years (Figure A.7). Still, while they clearly correlate with prior peer performance—either in terms of academics or behavior—bus effects appear to comprise more than just peer performance. This result stands in contrast to the assumption common in linear-in-means models of classroom peer effects, whereby peer performance is the only component of peer effects driving own performance. Second, we find little relationship between our estimates of bus effects and survey measures of school climate and student engagement. Third, neighborhood characteristics appear related to bus effects, particularly on academic outcomes, through all grade levels. For the most part, these relationships are intuitive. For example, having students who hail from neighborhoods with high rates of volunteering—a measure of social capital—is associated with positive academic bus effects. However, some neighborhood characteristics typically associated with improved outcomes are negatively associated with bus effects. While speculative, a potential explanation for this result is that for students from lower-income neighborhoods or lower-achieving schools, time on the bus may represent a relatively safe space for focusing on academic work.

Finally. we find that traditionally disadvantaged groups—Black and Hispanic students—are more often exposed to negative bus effects, suggesting that social interactions outside of school may perpetuate socioeconomic disadvantages (Figure A.10 and Table A.10). We also test for homophily in social interactions by race and gender (Appendix Section G). If the intensity of social interactions is greater among students of the same race or gender, estimates of bus effects that are specific to racial or gender groups should have more explanatory power than broader estimates. Our results provide little evidence of homophily (Figure A.11) .

5 Conclusion

We study how informal social interactions taking place outside of the classroom—namely on the school bus—affect student achievement and behavior. Methodologically, we show how recent ideas from teacher value-added estimation and experimental estimation of peer dynamics might extend to observational settings. Our results show that social interactions in informal settings may be important in shaping student learning outcomes, highlighting the need for research to better account for the various out-of-school settings to which students are exposed. This is all the more important since our results suggest that social interactions in informal settings such as the school bus may amplify socioeconomic disparities.

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Appendices

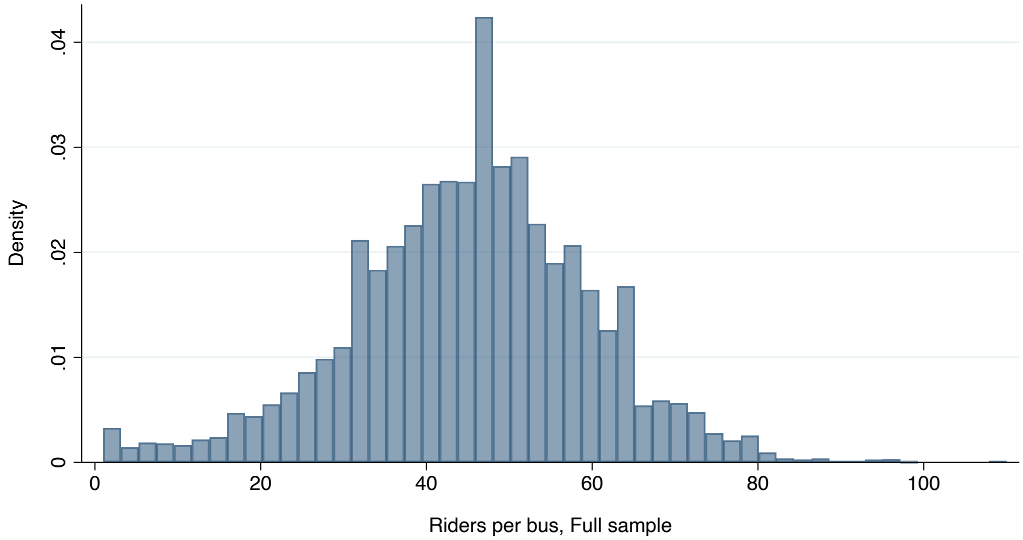
A Data appendix and institutional details

A.1 Data used in main analyses

We use multiple sources of administrative data from a single school district to estimate our main bus peer effects and supplement our analyses with additional sources drawn from Opportunity Insights (Chetty et al., 2018, 2022) and results from the district's Student Engagement Instrument (SEI) (Appleton et al., 2006) survey collection. Our key data source is bus ridership information for all students in the district over the four-year period spanning the academic years 2015-16 to 2018-19. To these records we merge person-period level information from student administrative files, test scores, course enrollments, grade point average, and disciplinary incidents. We discuss analysis file construction in more detail below.

Bus ridership records. The district's transportation department maintains student-level bus ridership information for all students assigned to ride the bus each academic year. To appear in ridership records, families request transportation service at the start of each academic year. Each student record has associated identifiers for stops, runs, and routes. "Stops" refer to each time a bus makes a pickup or dropoff at a home or stop. "Runs" refer to the route that each bus takes that includes a start time from the first pickup to the end time at the last dropoff. "Routes" capture all the runs that an individual bus makes over the course of the school day. To identify student and peer assignment to buses, we utilize run IDs. We restrict our analyses to riders with both morning and afternoon runs, which constitute roughly 94% of all riders. While we cannot confirm whether a student assigned to a bus actually rides the bus, we are confident of ridership fidelity for two reasons. First, the district maintains active ridership rolls from the start of school until November, when it finalizes ridership records. During this time, it removes students from transportation rolls who were initially assigned to a bus but did not ride during this period and it adds students who did not initially request transportation but did so later in the fall semester. Second, the state's transportation vendor, the Institute for Transportation Research and Education at North Carolina State University, informed us that our particular site district, Wake County, has maintained among the most accurate ridership records in the state.

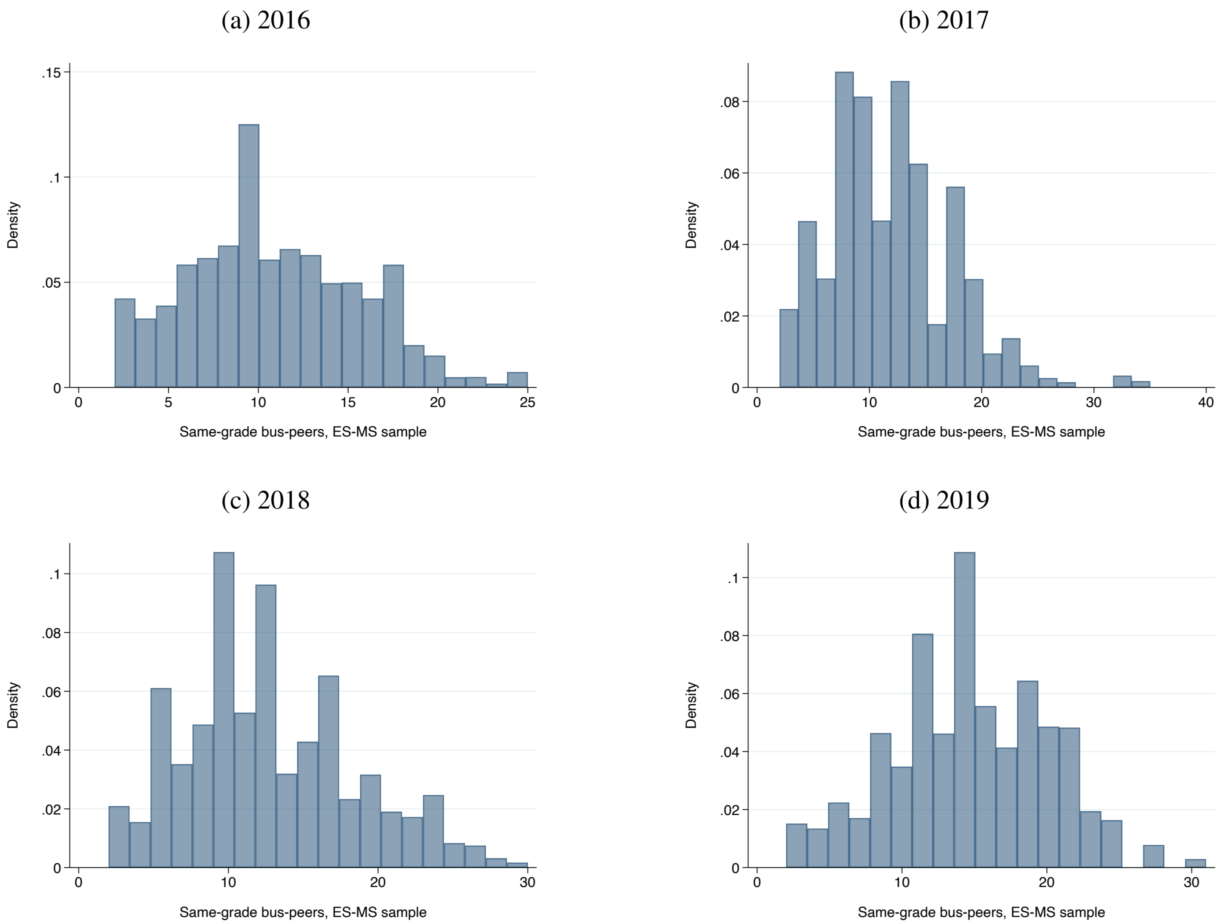
Figure A.1: Distribution of bus riders



Notes: This figure includes all students who ride a morning and afternoon bus The plot omits one-way riders, which represents 10% of to-school riders and 4% of from-school riders.

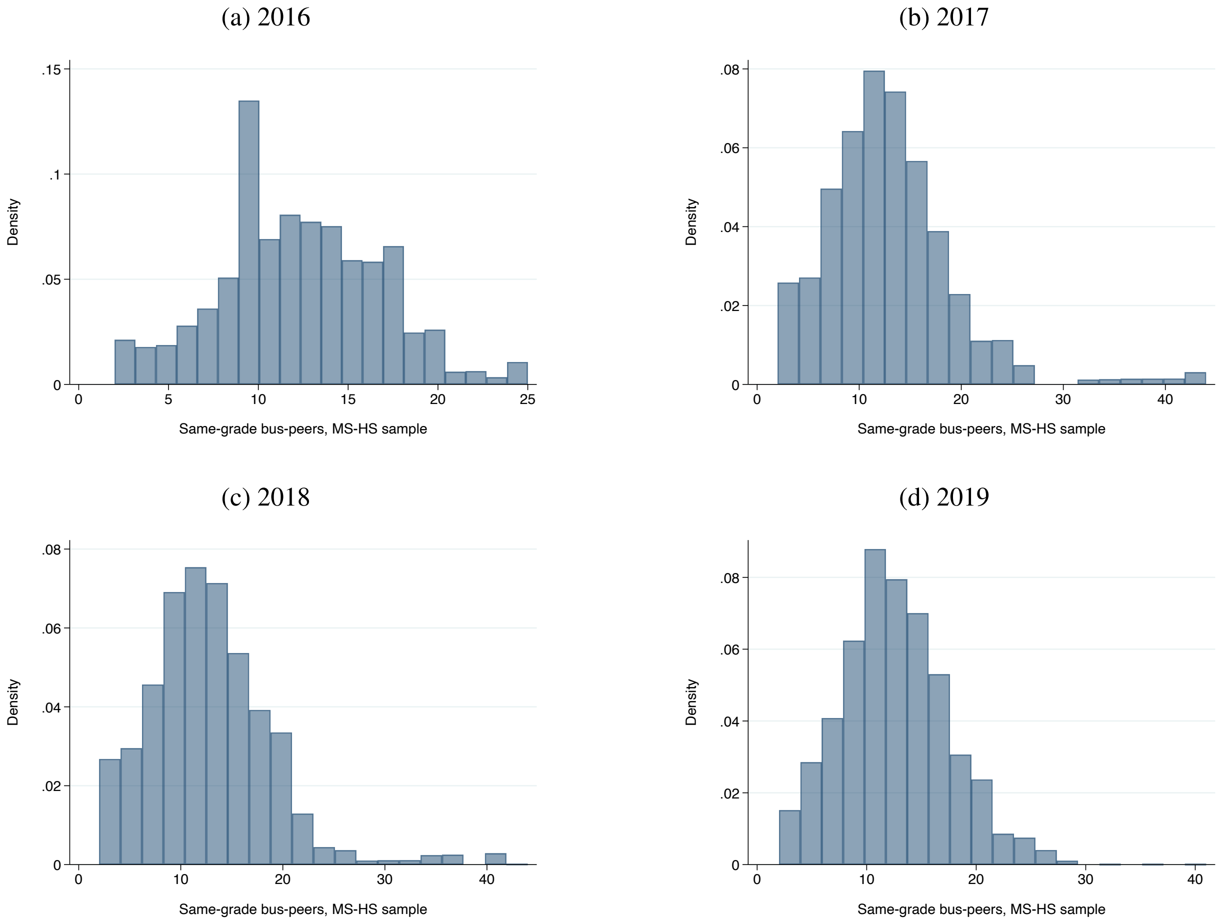
Appendix Figures A.2 and A.3, below, display the distributions of same-grade bus-peers per year. The number of same-grade bus-peers ranges from 12-13 across all plots and matches the corresponding mean values presented in Table 1.

Figure A.2: Distribution of same-grade bus-peers, elementary-middle sample



Notes: Each histogram displays the distribution of same-grade bus-peers for each year of the elementary school-middle school analytic sample.

Figure A.3: Distribution of same-grade bus-peers, middle-high sample



Notes: Each histogram displays the distribution of same-grade bus-peers for each year of the middle school-high school analytic sample.

Student information system (SIS) records. We merge bus ridership records to the district's student information system (SIS) records, which include data for every student in the district—bus riders and non-riders alike. These SIS records include indicators for enrollment, year, grade, sex, demographics, and special status (e.g., English language learner, academically gifted status, etc.). SIS records are unique by person-period, and thus bus records for each student merge as unique matches on year and student identifier. During this merge, we distinguish between riders (those who originate in transportation records) and non-riders in order to create Table 1. Appendix Table A.1 includes all year-by-grade cohorts used in the analysis file that result from this merge.

Test scores and grade point average (GPA). We utilize two main outcomes in our analyses. The first outcome captures cognitive ability (e.g., achievement) and the second captures non-cognitive ability (e.g., behavior). For elementary and middle school students—those in grades 3-8—we construct a single achievement index using an equally-weighted mean of mathematics and reading scores drawn from North Carolina's End-of-Grade (EOG) tests. The state administers EOG tests in both subjects to all test-eligible students (> 95% of all enrollees) in the mandated tested grades 3-8. We use factor analysis to reduce both tests to a single index and standardize the index to have a mean of zero and unit standard deviation. High school students are administered End-of-Course (EOC) tests at various enrollment spells and, thus, do not necessarily appear for all students in our four-year analytic sample. Instead, we use grade point average (GPA), which is a weighted average of course grades. While there may exist variation in how teachers assign grades, we observe relatively consistent between-school distributions of GPA across years. As with test scores, we standardize GPA to have a mean of zero and unit standard deviation.

Behavior. We use three separate behavioral data sources to construct a single index for behavior. The first source consists of daily absences, which we aggregate up to a single count measure for each student. The second source consists of tardies, which are assigned when students do not appear for homeroom without an excuse or are late to a subsequent class. The third is short-term suspensions, which is a moderately severe disciplinary event that is less severe than long-term suspensions and far less severe than expulsions. Since the latter two incidents appear so rarely in our data—especially among younger students—we omit them from the construction of our index. As with the achievement index, we reduce the values of these three measures to a single index using factor analysis.

A.2 Data used in supplemental analyses

In our supplemental analyses, we estimate classroom peer effects in order to compare the magnitude and precision of our bus effects to this commonly estimated linear-in-means approach to measuring peer effects. We also regress our main effects on three sets of variables that capture potential mechanisms stemming from average neighborhood, bus, and school characteristics. To construct average neighborhood characteristics, we link a range of indicators from Opportunity Insights to each student's U.S. Census tract. To construct average bus and classroom characteristics, we aggregate a combination of existing sources referenced above (e.g., sex, demographics, ride time, mean achievement and behavior, share of bus-peers in class) and add information from the Student Engagement Instrument (SEI).

Course enrollments. We use course enrollment data to measure the extent that students who share the bus together also share classes together. We also use course enrollment information to construct mean achievement levels for each student's classroom peers so that we can compare our bus peer effects to a commonly estimated, linear-in-means approximation of classroom peer effects. Course enrollment information includes course codes for each course that a student is assigned to during each academic year. For this supplementary analysis, we use as our dependent variable one's own current mean achievement (the same academic index as in our main analyses) and as our independent variable the leave-out, prior average academic performance of each student's current classroom peers.

Opportunity Insights. We use publicly available files from Opportunity Insights in order to estimate the relationship between our main bus effects and neighborhood characteristics. Specifically, we link Opportunity Atlas (Chetty et al., 2018) indicators at the level of U.S. Census tract to corresponding student addresses that fall with in the same geographic tract. In sum, we identified 16 variables that could theoretically shed light on our main bus effects.

Student Engagement Instrument (SEI). Researchers at the University of Minnesota developed the Student Engagement Instrument (SEI) (Appleton et al., 2006) as a companion survey to the widely implemented Check and Connect intervention that served U.S. adolescents at risk of dropout (e.g., See Anderson et al., 2004). The survey includes 32 Likert-style survey items across six validated domains, four of which we use for this supplementary set of analyses: Teacher–Student Relationships, Control and Relevance of School Work, Peer Support for Learning, and Family Support for Learning. We use factor analysis to reduce each domain's set of items to a single index and then standardized each index to have a mean of zero and unit standard deviation. Note: The district supplemented the SEI with a battery of civic engagement items drawn from Flanagan et al. (2007), which we also include here.

Figure A.4: District school bus routing and bus stop regulations

Regulation Code: 7125 R&P School Bus Routing and Bus Stops

A. The following goals are established to keep student ride time to a minimum.

1. Less than forty-five (45) minutes one-way ride time should be expected for most students.

2. Goals for one-way ride times:

- Proximity Elementary Students less than one hour
- Proximity Secondary Students less than one hour
- Magnet Students, Application students, students attending school not on their choice list, and students attending non-proximate schools - Forty-five (45) minutes in addition to the above times.

B. Number of students on buses: students are assigned based upon the following load limits:

Bus Load Limits				
Bus Size # of seats	**# students Elementary**	**# students Middle**	**# students High**	**# students Middle & High**
12	36	30	24	24
16	48	40	32	32
18	54	45	36	36
20	60	50	40	40
22	66	55	44	44
24	72	60	48	48
26	78	65	52	52

Notes: The above screenshot summarizes regulations that follow from WCPSS Board of Education Policy 7125, Section C: "Number of students on buses." The district's policy archive can be found at https://www.wcpss.net/schoolboard.

Table A.1: Grade-year cohorts included in estimation sample

	Elementary-Middle Sample				Middle-High Sample			
	2016	2017	2018	2019	2016	2017	2018	2019
Grade 3	c1							
Grade 4	c2	c1						
Grade 5	C3	C2	C1					
Grade 6		C3	C2	C1	c1			
Grade 7			c3	c2	c2	c1		
Grade 8				c3	C3	C2	C1	
Grade 9						C3	C2	C1
Grade 10							c3	c2
Grade 11								c3

Notes: Cells denote grade-year combinations. We define cohorts as consisting of students who switch buses across grade levels from elementary to middle school (left panel) or from middle school to high school (right panel). The estimation sample consists of these cohorts (upper-case C's) plus any observations for those same students that occur before and/or after a bus switch (lower-case c's). Within each estimation sample, students appear no more than five times (i.e., students are unique by grade-year within samples).

Table A.2: Elementary-middle school outcome correlation matrix

	Academic Index	Math	Reading	Behavior Index	Absences	Suspensions	Tardies
Academic	1						
Math	0.93	1					
Reading	0.93	0.72	1				
Behavior	0.21	0.23	0.16	1			
Absences	-0.20	-0.21	-0.15	-0.88	1		
Suspensions	-0.11	-0.11	-0.10	-0.12	0.12	1	
Tardies	-0.14	-0.15	-0.10	-0.65	0.27	0.06	1

Notes: This table presents the correlation matrix between academic and behavioral outcomes for students in the elementary-middle school sample.

Table A.3: Middle-high school outcome correlation matrix

	Academic Index	Behavior Index	Absences	Suspensions	Tardies
Academic	1				
Behavior	0.44	1			
Absences	-0.38	-0.86	1		
Suspensions	-0.17	-0.19	0.17	1	
Tardies	-0.35	-0.69	0.28	0.09	1

Notes: This table presents the correlation matrix between academic and behavioral outcomes for students in the middle-high school sample.

Table A.4: Middle-high school outcome correlation matrix

	Academic Index	Behavior Index	Early HS graduate	On-time HS graduate	Late HS graduate
Academic	1				
Behavior	0.61	1			
Early HS graduate	0.03	0.00	1		
On-time HS graduate	0.51	0.48	-0.45	1	
Late HS graduate	0.02	0.01	-0.01	-0.01	1

Notes: This table presents the correlation matrix among academic, behavioral, and downstream outcomes for unique 9th graders in the middle-high school sample.

B Conceptual framework

To provide a framework for our empirical study, we draw from theory on the technology of skill development (Cunha and Heckman, 2007; Jackson, 2018) and social interactions (Manski, 1993; Blume et al., 2015). Drawing from this theory, we formalize our approach to account for the following ideas: 1) skills can be developed across both cognitive and non-cognitive dimensions (which, for simplicity, we term *academics* and *behavior*), 2) social interactions with other students can contribute to the development of these skills, and 3) the technology of skill development might vary across grade-levels. We build the following model to capture these ideas.

We begin with the individual. Upon entering a grade, each student i has a stock of academic and behavioral ability described by vector $v_i = (v_{Ai}, v_{Bi})$, where the subscripts A and B denote academic and behavioral dimensions.

Students interact with each other in various settings. These social interactions may lead individuals to change their own behavior. Manski (1993) differentiates between two different types of social interactions: *exogenous (contextual)* and *endogenous*.[1] In the first, the exogenous or fixed characteristics of others—for example, another student's socioeconomic status—affect one's own behavior. In contrast, in endogenous interactions, the behavior of individuals in a group is simultaneously determined through social dynamics—potentially stemming from social pressure, conformity, or group norms, as studied by Bursztyn and Jensen (2015).

For example, if a student acts out on the bus by trying to attract the attention of their peers, both the student and their peers may suffer academically as a result of their inability to concentrate. In this case, the student acting out might not have were it not for the possibility of their peers' attention, and the other students would not have been distracted were it not for the student acting out. This is an endogenous interaction: it is impossible to isolate the direction of the causal arrows. Nonetheless, we want to include these in our estimates of the effects of social interactions.

Our context, the bus ride (b) to and from school, may include both types of social interactions—and we do not attempt to separate the two interactions on the bus that take place through the repeated contact of a small group of students. Thus, effects of social interactions on the bus may stem primarily from endogenous interactions.[2]

Each bus has distinct social dynamics (ω_b) across academic and behavioral dimensions, $\omega_b = (\omega_A, \omega_B)$.[3] For example, academic achievement could be affected if it is (or is not) desirable to spend time on the bus studying, or if students compare grades with their peers on the bus. Likewise, behavior could be affected if students are induced to participate in risky behaviors. We note that while

[1] See Blume et al. (2015) for a more recent discussion.

[2] While we believe that social dynamics on the bus stem primarily from interactions with other students, these interactions are likely mediated by other factors, such as the bus driver or the time spent on the bus.

[3] This model builds from Jackson (2018).

these interactions might be instigated and dynamics formed by sharing the bus to and from school, interactions among sets of bus peers can extend to neighborhoods, bus stops, and the classroom.

Still, not all students need to respond to the group dynamics on the bus in the same way.[4] The effects of bus b on student i are a function of social interactions on a bus (ω_b) and a student's responsiveness (D_i) to these interactions across both dimensions (A and B), such that $\omega_{ib} = D_i \omega_b$.

At the end of a grade, student skills develop such that their skills (α_{ib}) are a function of their ability stock (v_i), the dynamics on the bus (ω_{ib}), and other factors including (I_s), for example, school inputs, $\alpha_{ib} = v_i + \omega_{ib} + I_s$.[5]

Skills (Y_i) are observed, with error (ε_{ib}), through metrics such as disciplinary infractions or grades. The extent to which any observable measure of student skills is shaped by underlying ability across academics and behavior is represented by $\beta = (\beta_A, \beta_B)^T$.

$$Y_{ib} = \alpha_{ib}^T \beta_s + \varepsilon_{ib} \equiv (v_i + \omega_{ib} + I_s)^T \begin{pmatrix} \beta_A \\ \beta_B \end{pmatrix} + \varepsilon_{ib} \tag{A.1}$$

Our object of interest is how a particular grouping of people causes its members to behave differently than they might in other contexts. This sits well with our intuition that an individual student does not always cause others around them to behave in the same way. For example, a student who excels at sports may have a different effect on others when they are surrounded by students who care about sports compared to when they are surrounded by students who care about grades (see Bursztyn et al., 2019).

We consider what we call "bus effects" (μ_b) to be the effect of social interactions on bus b on skill Y_z for the average student $\mu_{zb} = E[\omega_{ib}]^T \beta_z$. This is a measure of the average divergence from students' prior performance when interacting with this particular set of people.

Standardizing μ_{zb} to have a mean of zero and standard deviation of one in both childhood and teenage years, we are interested in the how a one standard deviation change in bus dynamics affects student performance and whether this effect is similar for children of different ages.

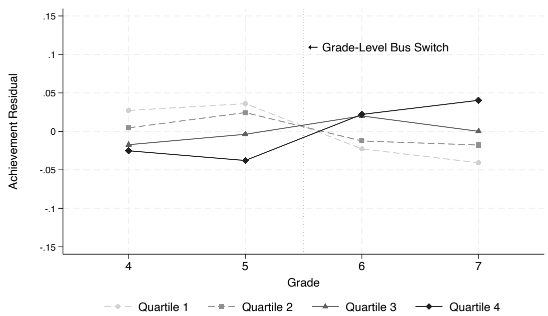
[4] Each student responds to the dynamics on the bus across academic and behavioral dimensions. This might be formally represented by the matrix $D_i = \begin{bmatrix} D_{Ai} & 0 \\ 0 & D_{Bi} \end{bmatrix}$. While it is possible that the behavioral dynamics affect a student's academic performance, or vice-versa, for simplicity we set the off-diagonals to zero. This is consistent with the theoretical framing and results from Jackson (2018) who finds that teachers tend to have distinct effects on academic performance and behavior.

[5] See Appendix D of Jackson (2018) for proof of additive separability.

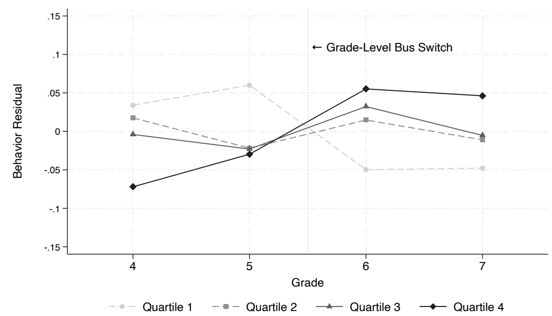
C Validating our empirical strategy

Figure A.5: Validation of empirical strategy, following Card et al. (2018)

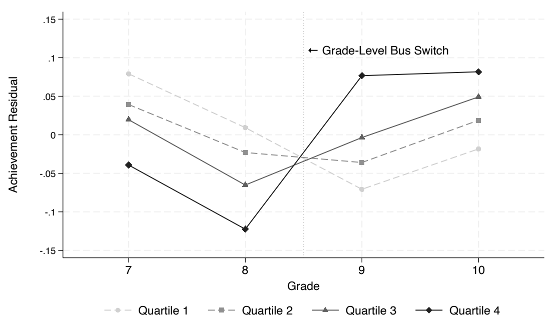
(a) Elementary-middle school academic achievement



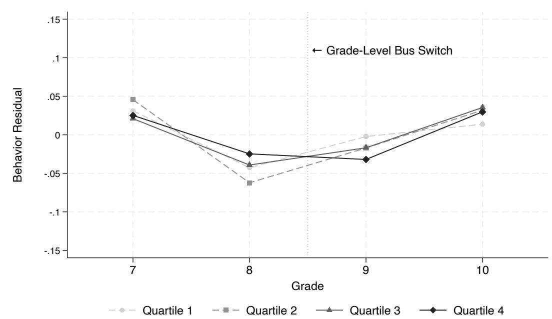
(b) Elementary-middle school behavior



(c) Middle-high school academic achievement



(d) Middle-high school behavior



Notes: These figures probe for the validity of our empirical approach. Following Card et al. (2018), we plot the residual in student performance—after accounting for student, school-by-school-pair, grade, and year fixed effects—for students who experience different magnitudes of bus effects between their elementary and middle, or middle and high schools. So that we can observe at least two years of outcomes before and after the bus switch, we focus on the cohorts that we first observe in 4th and 7th grades in our ES-MS and MS-HS samples, respectively. We group students into four equal-sized groups based on the magnitude of the difference in bus effects they experience. Quartile one is comprised of students who are in a relatively positive bus in their first school, and a relatively negative bus in their second school. Conversely, quartile four is comprised of students who are in a relatively negative bus in their first school, and a relatively positive bus in their second school.

D Benchmarking main estimates to same-sample classroom-based peer effects

How do the effects of informal social interactions among students who ride the bus together compare to more traditional estimates of peer effects in the classroom? The vastly different settings, estimation samples, outcome measures, and identifying assumptions used in different papers on peer effects in academic settings make it hard to synthesize specific estimates from the literature to use as a benchmark for our own. Instead, to provide a benchmark for our estimates of the effects of bus-peers, we use the same sample and outcome measures to estimate a more traditional form of peer effects in the classroom.

To benchmark our estimates, we build on a commonly used form of classroom peer effects which studies how the observable characteristics of a student's classmates affect a student's own performance. For simplicity, we take advantage of our longitudinal student data and adapt a linear-in-means approach to estimate how the past performance of classmates affects student performance and behavior, conditional on the student's own past performance. (See, for example, Sacerdote (2011) for a discussion of the literature on linear-in-means estimation, including critiques of the approach.) We specify our model as follows:

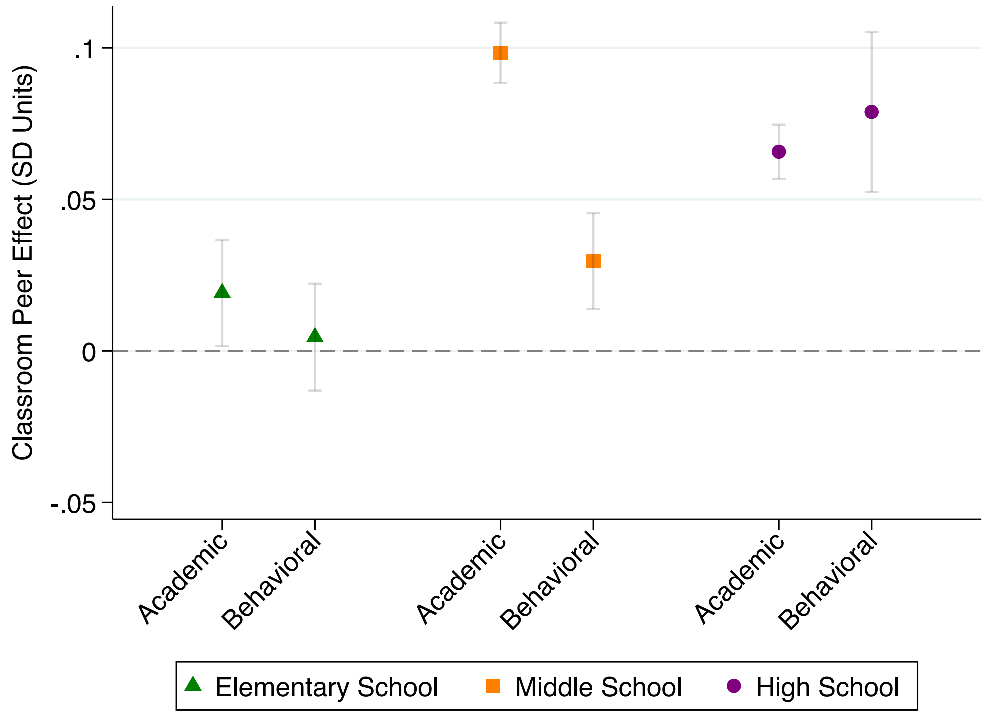
$$Y_{icsgt} = \alpha_i + \beta \bar{Y}_{-i,cs,t-1} + \lambda_{sgt} + \epsilon_{icsgt} \tag{A.2}$$

In equation A.2, we measure the outcomes of student i in classroom c in prior years, as well as a vector of fixed effects for school, grade, and year (λ_{sgt}). The key independent variable in this regression is a standardized measure of the mean outcome of student i's peers from the prior year. The coefficient of interest, β, measures how much a one-standard deviation shift in the mean performance of a student's classroom peers affects student i's own performance. One way this model tackles some of the problems noted in the literature on linear-in-means models is that the longitudinal nature of our data allows for us to include a measure of student fixed effects, which, as noted in the literature on teacher effects, can be vital for preventing bias associated with how students are allocated to different classes (Chetty et al., 2014). This literature typically finds that conditional on a student's own past performance, the allocation of classes can be interpreted to be as good as random within schools.

As shown in Appendix Figure A.6, in elementary school, a student's classmates have little effect on either the academic performance or behavior of students in elementary school (grades four and five). In middle and high school, the effect of a one standard deviation change in classmate outcomes on own performance and behavior fall between 0.03 and 0.10 SD with, if anything, slightly larger effects on academics than on behavioral outcomes. Like our bus effects, these classroom effects—well within the typical estimates from the existing literature on classroom peer effects (Sacerdote, 2011)—suggest that peers matter more in adolescent than early years. While it can be hard to compare the magnitudes of estimates by relying on different estimation strategies directly, it is notable that these effects are not much larger than our estimates of bus peer effects, which fall within 0.05 SD and 0.08 SD in middle and high school. One potential reason why these estimates of classroom peer effects are not much larger than those of bus peer effects could be due to the fact that classroom peer effects are restricted to those related to a linear measure of observed peer ability. Perhaps less surprisingly, while the classroom peer effects are mostly more related to academic performance rather than behavior, the bus peer effects include behavioral outcomes.

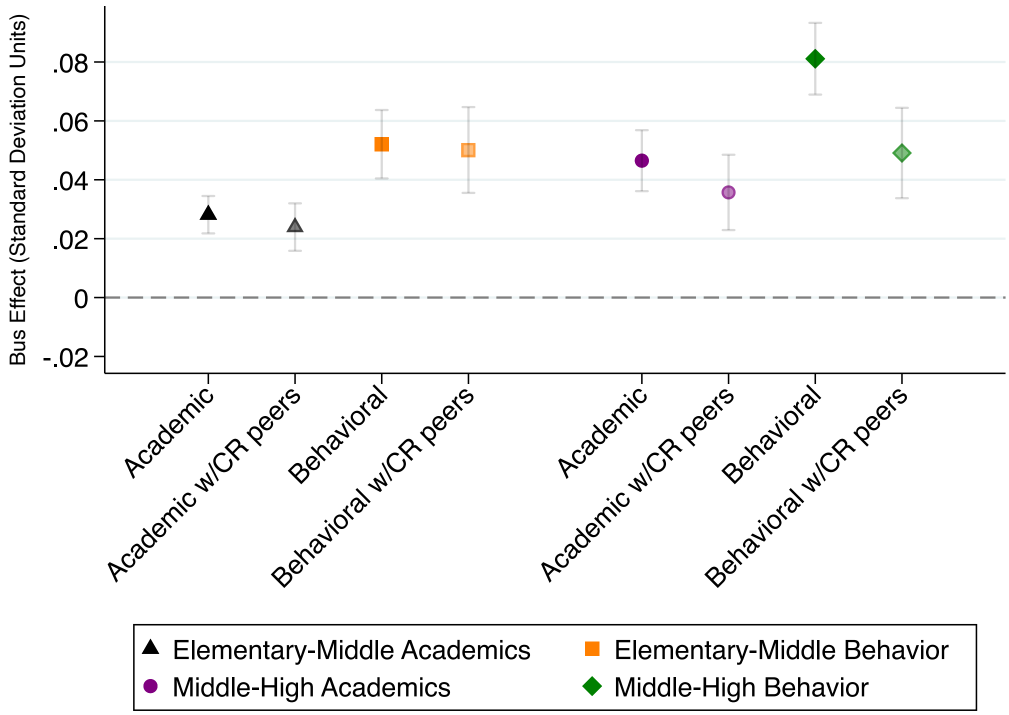
When we include measures of classroom peer ability in our main estimating equation, the elementary and middle school estimates remain unchanged, while we see the middle and high school estimates decrease (Figure A.7). This could be because the bus effects are partly driven by interactions in the classroom. Alternatively, this could also be because there is more scope for selection into classes in middle and high school, and bus peers could be endogenous with classroom peers.

Figure A.6: Linear-in-means peer effects estimates of classroom peers



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from the regression described in Equation A.2. This regression aims to estimate the relationship between a standard deviation change in the academic ability of a student's classroom peers, as measured in the prior year. All regressions include individual, school, year, and grade fixed effects. Standard errors are clustered at the classroom level.

Figure A.7: Main effects and main effects conditional on classroom peer academic performance



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects. All regressions include fixed effects for individual, school-by-school-pair, grade, and year. Standard errors are clustered at the bus-group level. Additionally, all regressions denoted "… w/CR peers" add controls for classroom peer ability as measured by prior performance.

E Main effects, drivers, and components

Table A.5: Bus effects on academic and behavioral outcomes

	Academic index			Behavioral index		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary-Middle Sample			
Bus-effects						
Academic	0.0281***		0.0280***	0.0107**		0.0060
	(0.0032)		(0.0032)	(0.0049)		(0.0032)
Behavioral		0.004	0.0014		0.0521***	0.0515***
		(0.0030)	(0.0030)		(0.0059)	(0.0060)
Observations	42,165	42,200	42,165	44,007	44,055	44,007
			Panel B: Middle-High Sample			
Bus-effects						
Academic	0.0465***		0.0449***	0.0098		-0.0009
	(0.0053)		(0.0053)	(0.0070)		(0.0053)
Behavioral		0.0166***	0.0129***		0.0811***	0.0825***
		(0.0041)	(0.0040)		(0.0062)	(0.0063)
Observations	44,221	44,301	44,221	46,926	47,181	46,926

Notes: Significance levels (* = 0.10, ** = 0.05, *** = 0.01).

Notes: Panels A and B distinguish two separate analytic samples by grade-level pairs, as identification is based on student bus switching across grade levels. Each column includes two separate regressions modeling an outcome on a bus effect (Equation 6). Columns (1)-(3) model the same academic outcome measure as a function of the academic bus effect (1), behavior bus effect (2), and both bus effects (3). The academic outcome measure is an index comprised of math and reading test scores in Panel A and grade point average (GPA) in Panel B. Columns (4)-(6) model the behavior outcome measure as a function of the academic bus effect (4), behavior bus effect (5), and both bus effects (6). The behavior outcome measure is an index comprised of tardies, absences, and short-term suspensions. All models include fixed effects for student, grade, year, and school-by-school-pair—with elementary-middle school pairs in Panel A and middle-high school pairs in Panel B. Robust standard errors in parenthesis are clustered at the bus-group level.

Table A.6: Unshrunken bus effects on academic and behavioral outcomes

	Academic index			Behavioral index		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary-Middle Sample			
Bus-effects						
Academic	0.0267***		0.0265***	0.0100**		0.0062
	(0.0029)		(0.0029)	(0.0046)		(0.0029)
Behavioral		0.004	0.0016		0.0446***	0.0439***
		(0.0028)	(0.0028)		(0.0054)	(0.0055)
Observations	45,606	45,639	45,606	48,214	48,260	48,214
			Panel B: Middle-High Sample			
Bus-effects						
Academic	0.0374***		0.0360***	0.0086		-0.0008
	(0.0042)		(0.0042)	(0.0059)		(0.0042)
Behavioral		0.0153***	0.0118***		0.0706***	0.0718***
		(0.0036)	(0.0036)		(0.0057)	(0.0058)
Observations	49,659	49,733	49,659	52,516	52,757	52,516

Notes: Significance levels (* = 0.10, ** = 0.05, *** = 0.01).

Notes: Panels A and B distinguish two separate analytic samples by grade-level pairs, as identification is based on student bus switching across grade levels. Each column includes two separate regressions modeling an outcome on an unshrunken bus effect (Equation 3). Columns (1)-(3) model the same academic outcome measure as a function of the academic bus effect (1), behavior bus effect (2), and both bus effects (3). The academic outcome measure is an index comprised of math and reading test scores in Panel A and grade point average (GPA) in Panel B. Columns (4)-(6) model the behavior outcome measure as a function of the academic bus effect (4), behavior bus effect (5), and both bus effects (6). The behavior outcome measure is an index comprised of tardies, absences, and short-term suspensions. All models include fixed effects for student, grade, school-by-school-pair, and year—with elementary-middle school pairs in Panel A and middle-high school pairs in Panel B. Robust standard errors in parenthesis are clustered at the bus-group level.

Table A.7: Components of main estimates

	Elementary-Middle		Middle-High	
	Academic bus effect	Behavioral bus effect	Academic bus effect	Behavioral bus effect
	(1)	(2)	(3)	(4)
Achievement index	0.028***	0.004	0.046***	0.017***
	(0.003)	(0.003)	(0.005)	(0.004)
Math achievement	0.038***	0.005	0.019*	-0.000
	(0.004)	(0.004)	(0.011)	(0.008)
Reading achievement	0.014***	0.002	-0.000	0.004
	(0.004)	(0.004)	(0.009)	(0.007)
Behavior index	0.011**	0.052***	0.010	0.081***
	(0.005)	(0.006)	(0.007)	(0.006)
Absences	-0.087**	-0.347***	-0.260***	-0.568***
	(0.037)	(0.045)	(0.066)	(0.057)
Short-term suspensions	-0.000	-0.004	-0.007***	0.003
	(0.002)	(0.003)	(0.003)	(0.003)
Tardies	-0.119***	-0.362***	0.429***	-1.178***
	(0.040)	(0.057)	(0.111)	(0.097)
Observations	44,007	44,055	46,926	47,181

Notes: Significance levels (* = 0.10, **= 0.05, *** = 0.01).

Notes: This table plots the coefficients obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects as well as components used to create each outcome index. All regressions include fixed effects for individual, school-by-school-pair, grade, and year. Columns 1 and 3 have leave-out-student estimates of academic achievement on the right hand side of the equation, while columns 2 and 4 have leave-out-student estimates of behavior on the right hand side of the equation. Middle-high achievement is a function of GPA only, so it does not have separate math and reading components.

F Associations of bus effects with neighborhood, bus, and school characteristics

Like estimates of teacher value-added or match effects from an AKM model, our estimates of informal social interactions on the bus (bus effects) are also a bit of a black box. Unlike linear-in-means estimates of peer effects, for example, our estimates are not simply a product of exposure to high-performing classmates. One way that researchers have begun to unpack the black box of teacher effects has been by correlating the value-added estimates with background characteristics that might be useful in explaining why certain teachers are effective while others are not (Barrios Fernández and Riudavets, 2021).

Similarly, we are interested in why some groupings of students who ride the bus together affect each other's academic or behavioral outcomes in positive ways while others do not. To fix ideas about what could be driving our bus effects, we organize our potential covariates into three categories: those related to the neighborhood, those related to the bus itself, and those related to the school.

The Neighborhood. There are several reasons why neighborhoods might be important in explaining the bus effects we estimate in this paper. First, perhaps the time spent on a bus is meaningful because of the neighborhood interactions the bus ride enables after school. If this is the case, buses that drop students off in potentially dangerous neighborhoods or those with less social capital might be associated with smaller bus effects. Conversely, if time on the bus substitutes for homes and neighborhoods as a place where students can complete homework or spend time in a safe space, it is also possible that students living in neighborhoods with less academic support might benefit from having time on the bus to devote to schoolwork and friendship formation.

To measure characteristics of neighborhoods, we link student administrative data based on their precise residential location to data made available by Chetty et al. (2018) and Chetty et al. (2022), which provide measures at the level of U.S. Census tract and zip code, respectively. We summarize these data in Appendix Table A.8 and how they correlate with our main outcomes in Appendix Table A.9. While some correlations appear counter-intuitive—for example, high incarceration rates are correlated with improved academic outcomes—most measures appear to provide intuitive and potentially valuable information regarding the relationship between neighborhoods and schools. These measures include variables associated with a neighborhood's social capital—such as the U.S. Census form return rate, mean commute time, membership in civic organisations, or volunteerism. Additionally, these variables include information on economic background covariates, such as poverty, employment, single-parent households, and economic mobility. For more information on how these data were collected and what they measure, we refer readers to the original papers by Chetty et al. (2018) and Chetty et al. (2022).

The Bus. An obvious setting to explore potential characteristics important in explaining the bus effects we estimate is the bus itself. One way in which characteristics of the bus might matter is through the composition of the students who ride the bus together. For example, a grouping of high-performing students may lead to increased time spent together talking about or working on academic material; or—as noted by social psychologists—the school bus may present a setting where students develop social skills (Galliger et al., 2009) or are exposed to bullying (Sampasa-Kanyinga et al., 2016; Walters et al., 2021). Alternatively, we might imagine that what matters regarding the bus are characteristics of the bus ride that might otherwise be independent of the students themselves, such as ride time. To measure factors related to the bus ride itself, we include bus-level means of student background characteristics, student performance, and student responses to surveys on various dimensions of school climate. We also include a measure of ride time.

The School. Schools may also be important in explaining bus-effects in several ways. First, the climate of the school—whether a focus on academics, or attention to student behavior—may translate to how students spend time on the bus. For example, students attending a school with higher average academic performance may spend more time studying on the bus. Another reason why schools might matter could be simply because it is in schools where students who ride the bus together spend time. To measure these types of characteristics associated with schools, we include measures of school-wide socioeconomic characteristics, academic performance, behavior, and survey responses on school climate. We also include variables that measure the extent that individuals who ride the bus together also share classes together during the school day.

Results. We fit simple regressions that examine the relationship between each of these variables and our four main estimates of bus-effects: elementary-middle school academic, elementary-middle school behavioral, middle-high school academic, and middle-high school behavioral. Each of these bivariate regressions is fit separately, with standardized variables, and standard errors clustered at the bus-group level. The results are reported in Appendix Figures A.8-A.9.

For students in elementary and middle school, bus effects on academic performance are highest among students from more affluent neighborhoods, those who ride the bus with higher performing peers, and those who attend higher performing schools. In contrast, bus effects on behavior are most highly predicted by the behavior of students who ride the bus together and less correlated with socio-economic characteristics.

For students in middle and high school, it appears that characteristics of students riding the bus together are less predictive of bus effects than the characteristics of the neighborhoods in which they live and particularly the schools they attend. For younger students, however, the behavioral outcomes of students who ride the bus together are relatively highly predictive of bus effects on behavioral outcomes.

Apparent in both samples of younger and older students, bus effects on behavioral measures are associated with lower behavioral outcomes among bus peers and in schools more broadly. While speculative, this suggests that the behavior of peers may affect a student's own behavior. In contrast, the pattern of results whereby bus effects on academic skills appear strongest in schools where students report less family support and are relatively unrelated to the academic performance of bus peers suggest that time on bus may function as a substitute for time at home to complete some school work—rather than serve as a function of the academic performance of peers on the bus.

Table A.8: Neighborhood descriptives from Opportunity Insights data

	Full sample (1)	Riders (2)	Non-riders (3)	ES-MS Sample (4)	MS-HS Sample (5)
			Panel A: Opportunity Atlas Data (Census-tract level)		
Census form return rate	81.27	80.98	81.65	80.79	81.39
	(6.01)	(5.99)	(6.02)	(6.02)	(5.70)
Mean commute time	27.96	28.21	27.63	28.31	28.52
	(4.37)	(4.23)	(4.52)	(4.22)	(4.18)
Employment rate	0.73	0.73	0.73	0.73	0.73
	(0.06)	(0.05)	(0.06)	(0.06)	(0.05)
Single-parent households	0.25	0.25	0.25	0.26	0.24
	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)
Below poverty line	0.09	0.09	0.08	0.09	0.08
	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
Population density	512.22	480.63	553.06	471.93	438.25
	(557.07)	(559.86)	(550.77)	(562.43)	(513.53)
Median household income	82,326.34	81,426.55	83,489.46	80,761.71	82,831.82
	(31,143.03)	(31,237.87)	(30,981.45)	(31,508.04)	(30,796.71)
College degree or higher	0.47	0.46	0.49	0.45	0.46
	(0.18)	(0.18)	(0.18)	(0.18)	(0.17)
Mean income rank at 24	0.42	0.42	0.43	0.41	0.42
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Incarceration rate	0.02	0.03	0.02	0.03	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
			Panel B: Social Capital Data (Zip-code level)		
Economic connectedness	0.95	0.95	0.96	0.95	0.95
	(0.15)	(0.16)	(0.15)	(0.15)	(0.15)
Neighborhood economic connectedness	1.15	1.14	1.17	1.15	1.15
	(0.48)	(0.49)	(0.45)	(0.48)	(0.48)
Network clustering	0.09	0.09	0.09	0.09	0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Network support ratio	0.82	0.83	0.82	0.82	0.82
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Civic organizations	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Volunteering rate	0.07	0.06	0.07	0.07	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	266,550	149,780	116,770	47,457	51,045
Students	82,705	41,535	41,170	12,342	13,247
Sets of same-grade bus-peers				3,848	3,758
Schools	189	186	187	134	62
Census tracts	377	278	332	189	194
Zip codes	44	43	42	35	33

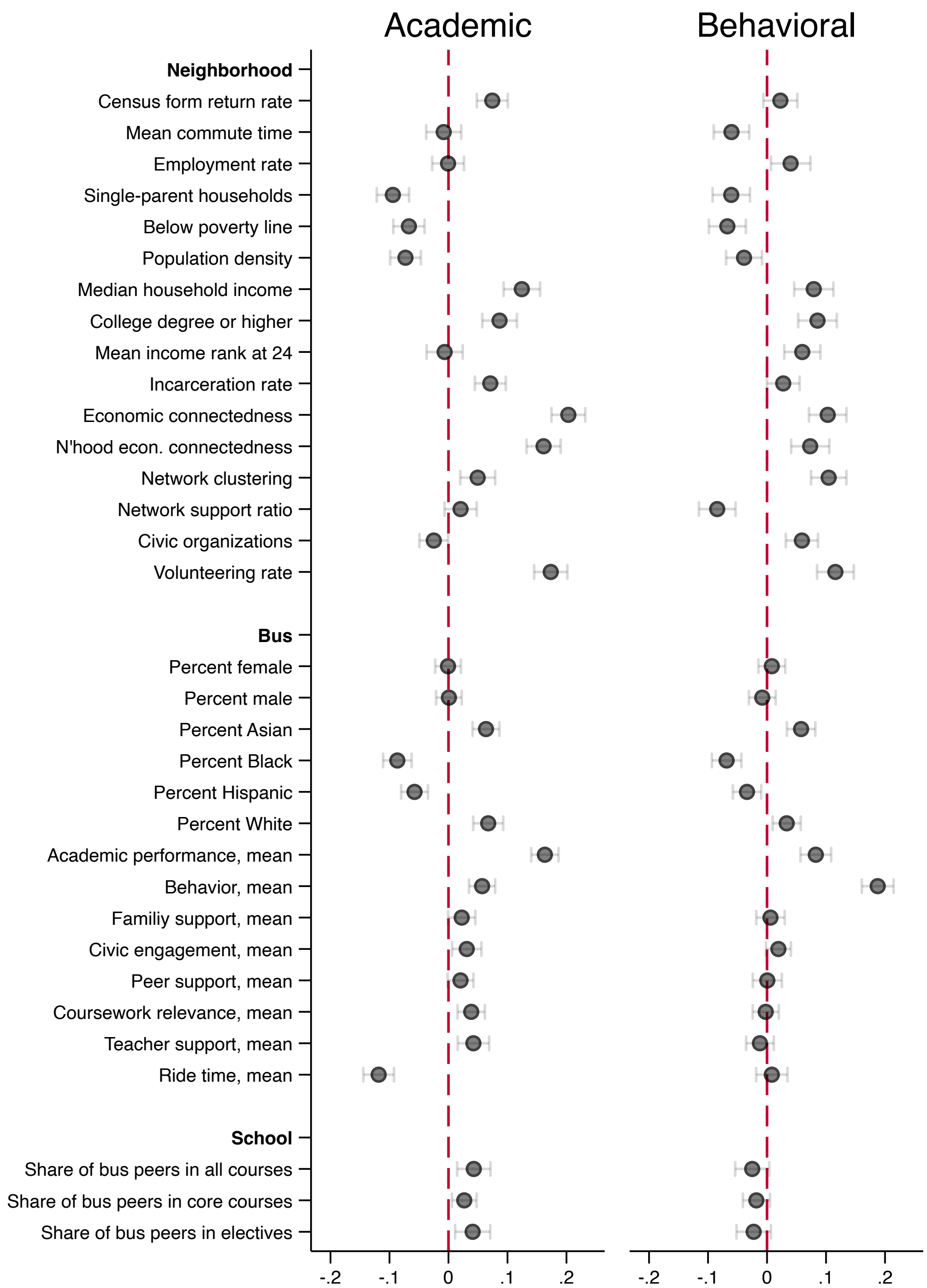
Notes: These descriptive statistics comes from linking the residential addresses of students to census-tract level data from Chetty et al. (2018) and zip-code level data from Chetty et al. (2022). Means and standard deviations are reported for background characteristics and outcomes for our full sample, bus-riders, non-riders, as well as our two estimation samples separately. The full sample consists of student-by-grade-by-year combinations that comprise each of three cohorts we follow (See Appendix Table A.1).

Table A.9: Correlations between neighborhood characteristics and outcomes

	Elementary-Middle		Middle-High	
	Academic	Behavioral	Academic	Behavioral
	(1)	(2)	(3)	(4)
	Panel A: Opportunity Atlas Data (Census-tract level)			
Census form return rate	0.35	0.10	0.34	0.15
Mean commute time	-0.02	-0.03	-0.01	-0.03
Employment rate	0.22	0.08	0.18	0.12
Single-parent households	-0.41	-0.12	-0.35	-0.16
Below poverty line	-0.38	-0.14	-0.33	-0.19
Population density	-0.16	-0.06	-0.12	-0.06
Median households income	0.49	0.16	0.44	0.22
College degree or higher	0.47	0.15	0.41	0.21
Mean household income rank	0.32	0.11	0.28	0.15
Fraction incarcerated	0.04	0.02	0.04	0.02
	Panel B: Social Capital Data (Zip-code level)			
Economic connectedness	0.48	0.15	0.42	0.20
Neighborhood economic connectedness	0.48	0.14	0.42	0.19
Network clustering	0.10	0.06	0.08	0.06
Network support ratio	-0.23	-0.09	-0.19	-0.12
Civic organizations	-0.13	-0.05	-0.11	-0.07
Volunteering rate	0.44	0.12	0.39	0.18
Observations	44,914	47,457	48,241	51,045
Students	11,941	12,342	12,811	13,247
Sets of same-grade bus-peers	3,848	3,848	3,758	3,758
Schools	134	134	62	62
Census tracts	189	189	194	194
Zip codes	35	35	33	33

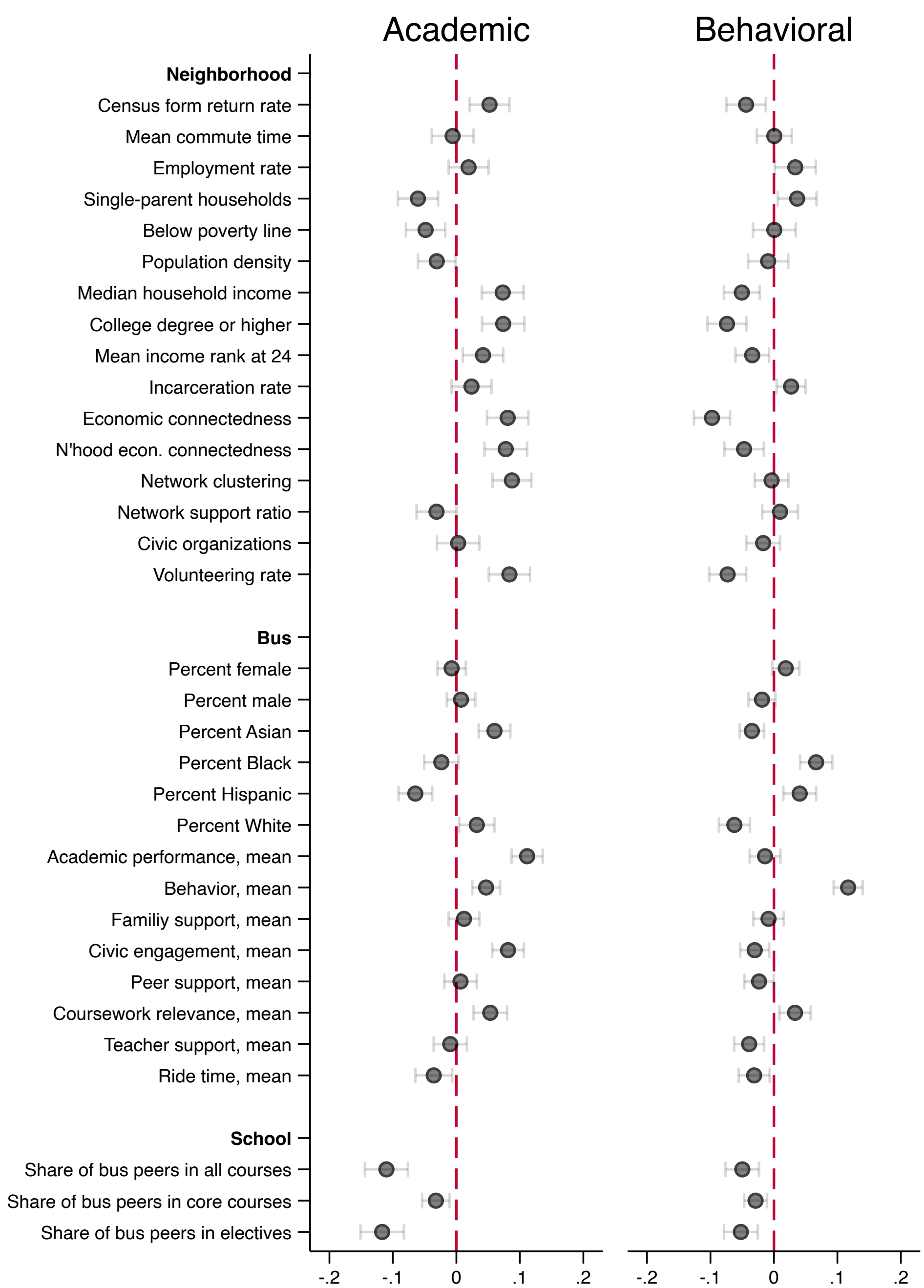
Notes: This table reports correlations coefficients between our main outcomes in both estimation samples and the neighborhood data described in Appendix Table A.8.

Figure A.8: Associations of elementary-middle school bus effects with neighborhood, bus, and school characteristics



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing standardized measures of neighborhood, bus, and school characteristics on our estimates of bus effects. Standard errors are clustered at the bus-group level.

Figure A.9: Associations of middle-high school bus effects with neighborhood, bus, and school characteristics



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing standardized measures of neighborhood, bus, and school characteristics on our estimates of bus effects. Standard errors are clustered at the bus-group level.

Table A.10: Main effects with select covariate interactions

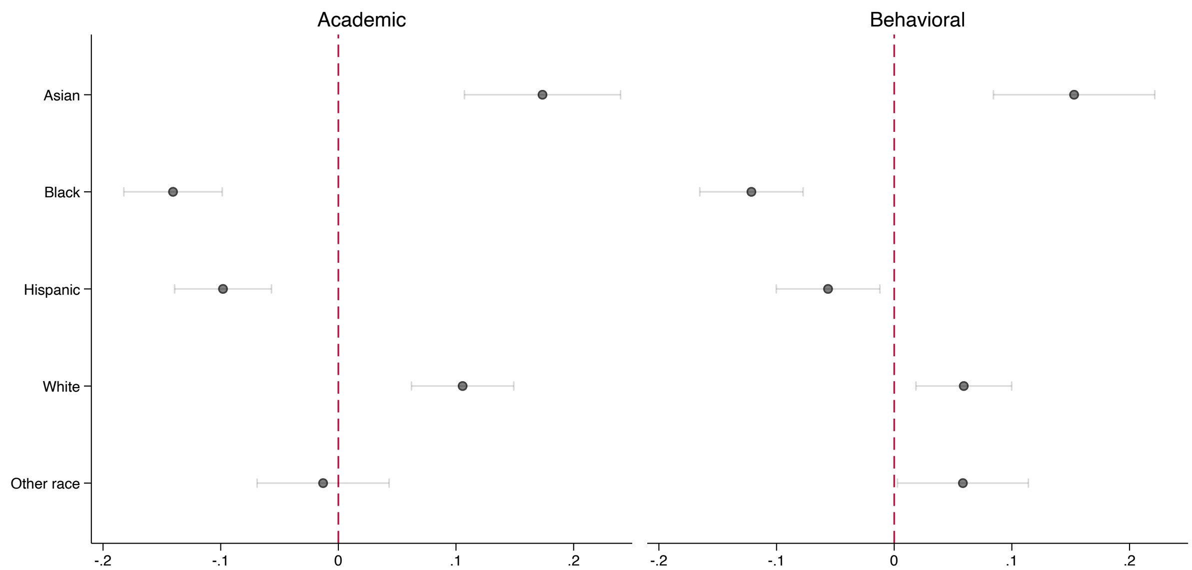
	Elementary-Middle		Middle-High	
	Academics	Behavior	Academics	Behavior
	(1)	(2)	(3)	(4)
Panel A: Male				
Bus effect	0.028***	0.045***	0.004	0.073***
	(0.004)	(0.008)	(0.006)	(0.008)
Male	-0.227*	-0.058	0.133	-0.041
	(0.136)	(0.106)	(0.103)	(0.095)
Bus x Male	0.001	0.013	0.087***	0.017
	(0.136)	(0.106)	(0.103)	(0.095)
Observations	42,165	44,055	44,221	47,181
Panel B: Nonwhite				
Bus effect	0.027***	0.044***	0.067***	0.032***
	(0.005)	(0.009)	(0.006)	(0.007)
Nonwhite	-0.029	-0.073	-0.219	-0.042
	(0.098)	(0.114)	(0.135)	(0.191)
Bus x Nonwhite	0.001	0.011	-0.033***	0.071***
	(0.098)	(0.114)	(0.135)	(0.191)
Observations	42,165	44,055	44,221	47,181
Panel C: Ride time				
Bus effect	0.040***	0.043***	0.057***	0.091***
	(0.005)	(0.009)	(0.007)	(0.010)
Ride time	-0.000***	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Bus x Ride time	-0.000***	0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	42,047	43,923	43,822	46,790
Panel D: School achievement				
Bus effect	0.024***	0.051***	0.039***	0.075***
	(0.003)	(0.006)	(0.005)	(0.006)
School achievement	0.143***	0.039**	0.237***	0.097***
	(0.013)	(0.020)	(0.019)	(0.025)
Bus x School achievement	0.024***	-0.030**	0.027***	-0.057***
	(0.013)	(0.020)	(0.019)	(0.025)
Observations	42,165	44,055	44,221	47,181
Panel E: Neighborhood median income				
Bus effect	0.028***	0.051***	0.048***	0.069***
	(0.003)	(0.006)	(0.005)	(0.006)
Neighborhood median income	0.010	0.016	-0.004	-0.011
	(0.009)	(0.019)	(0.011)	(0.015)
Bus x Neighborhood median income	0.001	-0.004	0.013***	-0.036***
	(0.009)	(0.019)	(0.011)	(0.015)
Observations	42,120	44,004	44,175	47,135

Notes: Significance levels (* = 0.10, ** = 0.05, *** = 0.01).

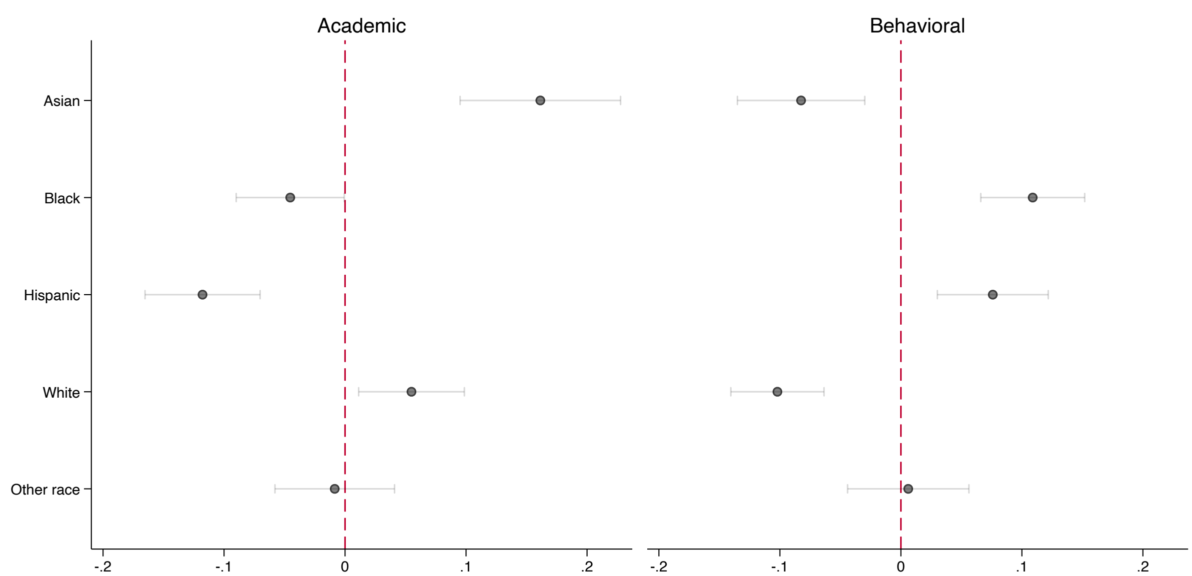
Notes: This table summarizes heterogeneity in our main estimates through interactions between main effects and select covariates.

Figure A.10: Associations of bus effects with student race and ethnicity

(a) Elementary-middle school academic achievement



(b) Middle-high school academic achievement



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing racial and ethnic characteristics on our estimates of bus effects. Standard errors are clustered at the bus-group level.

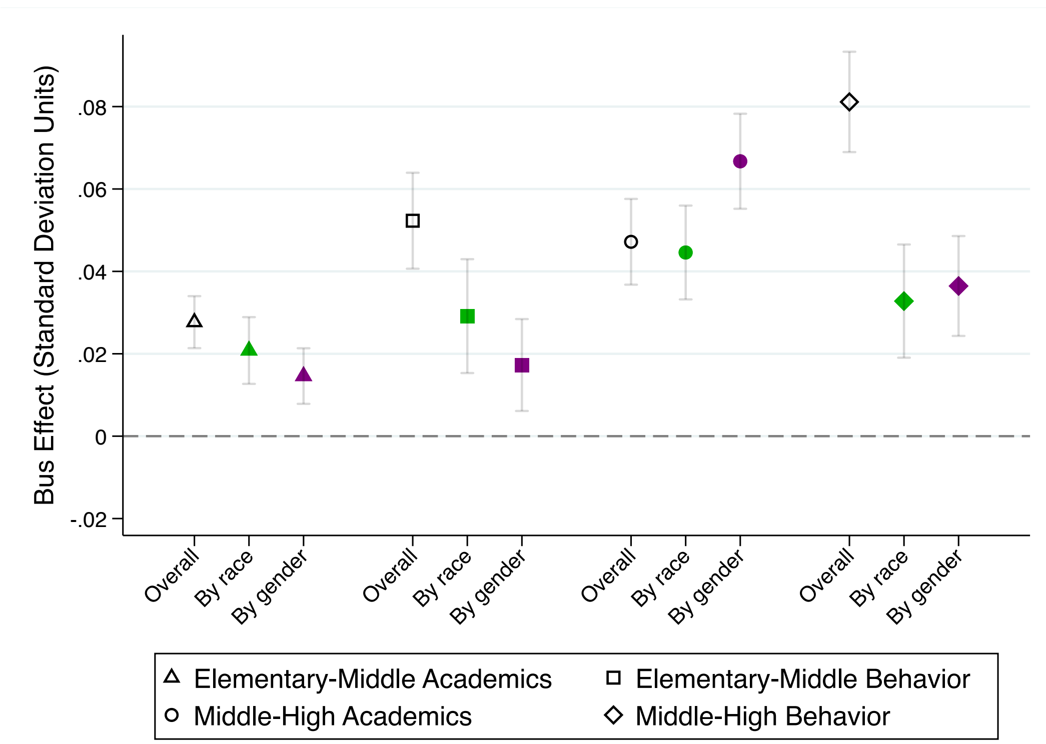
G Homophily by race and gender among bus peers

Prior research documenting homophily in social networks suggests that students are likely to spend time with individuals who are similar to themselves (Hoxby, 2000; Currarini et al., 2009; Bennett and Bergman, 2021).

To determine the extent to which homophily manifests in our setting, we test for whether students of the same race and gender are more likely to be affected by students with characteristics similar to themselves. We hypothesize that the intensity of social interactions are larger among students of the same race or gender who ride the bus together. To test whether or not this is the case, we replicate our main jackknife estimation strategy, but divide students into bus-peer groups based on dimensions of race and gender prior to fitting our models.

By and large, the results reported in Figure A.11 display point estimates which are not particularly different—and mostly not larger—than the main estimates, suggesting little evidence of self-segregation by gender or race.

Figure A.11: Homophily in social interactions



Notes: This figure plots the coefficients and 95 percent confidence intervals obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects. All regressions include fixed effects for individual, school(s), grade, and year. Standard errors are clustered at the bus-group level.