Informal social interactions, academic achievement and behavior

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Abstract

We study the effects of informal social interactions on academic achievement and behavior using idiosyncratic variation in peer groups stemming from changes in bus routes across elementary, middle, and high school. In early grades, a one standard-deviation change in the value-added of same-grade bus peers corresponds to a 0.01 SD change in academic performance and a 0.03 SD change in behavior; by high school, these magnitudes grow to 0.04 SD and 0.06 SD. These findings suggest that student interactions outside the classroom—especially in adolescence—may be an important factor in the education production function.

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Recent work has documented the importance of neighborhood context on educational and labor market outcomes (Chetty et al., 2016; Chetty and Hendren, 2018). While some work suggests that peers play a central role in explaining neighborhood effects (Deutscher, 2020), researchers across the social sciences are still working 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 (see Durlauf and Ioannides, 2010 or Sacerdote, 2011 for overviews). 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 later 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 not unique to 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.

We study the role of repeated informal social interactions on human capital development and introduce a novel way 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 unstudied component of the educational production function which often constitutes a period of time equivalent to roughly a class period.

We consider a model of social interactions where the ways in which students influence each other depends on the particular set of peers around them, and where peer culture can influence students in different ways (e.g., academics vs. behavior).[1] Our object of interest is how a particular grouping of people causes its members to behave differently than they might in other contexts.[2]

[1] 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 acted out were it not for the possibility of their peers' attention, and the other students would not have been distracted if it were 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.

[2] 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

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 parents choose neighborhoods based on their resources and preferences, and the decision of 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 take place in a number of ways and can be hard 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.[3] 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 predict 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, 2020; Isphording and Zölitz, 2020; Mulhern, 2020; Jackson et al., 2020).[4] But, 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 using data only from their peers. Our identifying assumption is that conditional on student, school-pair, year, and grade fixed-effects, variation in the residual of student performance common to students who ride the bus together is unrelated to factors apart from their bus-ride, broadly construed.[5]

To estimate our model, we use administrative data from North Carolina's largest school system where a majority of students ride the bus to and from school. On average, the informal social interactions we study take place among roughly five or six students, and last

when they are surrounded by a students who care about sports compared to when they are surrounded by students who care about grades (see Bursztyn et al., 2019).

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

[4]

See also prior 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.

[5]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 the effects of things besides 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.

for upwards of half an hour each day.[6] 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 0.01 standard deviations (SD) and behavior of 0.03 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 0.04 SD increase in academic performance and a 0.06 SD improvement in behavior.[7] Interestingly, we find that bus peers that affect academic achievement have almost no effect on behavior, and bus peers that affect behavior have no effect on achievement. We validate our estimates using the approach suggested by Card et al. (2018) in the worker-firm match literature.

Next, we test for homophily in social interactions.[8] If students are more likely to interact with other students of the same gender or race, we should expect the leave-out-estimators based on students with shared characteristics to be more predictive of changes in a students' own performance than those based on all bus peers. Our results support this hypothesis: when we estimate our model for gender and race subgroups, we find larger effects. These results suggest self-segregation by gender and race among bus peers in elementary and middle school. By high school, we find evidence consistent with persistent self-segregation by gender, but more variance in self-segregation by race.[9]

Our results offer several takeaways. First, informal social interactions among students are likely to have greater effects on behavioral rather than academic outcomes. Second, these out-of-classroom interactions appear more meaningful in adolescence than in childhood. Third, our findings suggest that social interactions among bus peers that affect academic achievement are distinct from those that affect behavior. Finally, we find evidence of homophily, suggesting that peer effects can be highly local within a broader group. Unfortunately, we

[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 time that these students spend together.

[7] As a point of reference, a one standard deviation change in teacher value-added results in a 0.14 SD change in student learning (Chetty et al., 2014), and smaller in work by Jackson (2018). Prior work on peer effects also examines non-academic outcomes—see, for example, Gaviria and Raphael (2001).

[8] See prior work on peer effects documenting homophily in social interactions by Hoxby (2000).

[9] Also, since these results suggest that the effects of bus peers vary among subgroups of students who ride the bus together, they help us understand the possible mechanisms underlying our results. For example, if the bus driver was contributing to the bus value-added estimates, we might not expect this effect to differ by subgroup.

lack sufficient statistical power to study how the effects of informal interactions on the school bus relate to observable characteristics related to that particular group of students; this is an area for future research.

Our work extends recent papers by Weidmann and Deming (2020) and Isphording and Zölitz (2020) who develop an innovative experimental approach to estimating peer effects in 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.[10] Where their approaches assume that an individual's effect on the group is constant across different settings or sets of peers (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.[11] Moreover, we show that this 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 suggest that social interactions in informal settings outside of school can have ramifications for what occurs within the classroom.[12] We also shed light on the potential channels through which granular levels of place matters. Agenda-setting work by Chetty et al. (2016) establishes the significance of a child's neighborhood as a determinant of labor market outcomes. A key observation of this research, and one corroborated by Jackson et al. (2020), is that neighborhood may be particularly important in adolescence. 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

[10] These types of situations are likely to be common. For example, when placed together, a group of competitive students may work to outshine one-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 between the students, potentially leading to behavioral problems.

[11] 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 (2020) 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 that the leader and those who met in that context contributed to that particular group dynamic.

[12] Interactions outside the classroom have been studied higher education (Sacerdote, 2001; Zimmerman, 2003; Marmaros and Sacerdote, 2006; Camargo et al., 2010).

in adolescence—may play a role (Deutscher, 2020; Agostinelli et al., 2020). By providing a close look at a context associated with and resembling interactions that take place in the neighborhood, we show that informal interactions with a highly localized set of peers shape educational trajectories, particularly in adolescence. These findings shed light on recent work suggesting that neighbors can influence patterns of higher educational choice (Goulas et al., 2018; Barrios Fernández, 2021).

Further, our results contribute 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; Edin et al., 2017; Barrera-Osorio et al., 2020), 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 suggests 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 that behavior may be malleable beyond childhood.

1 Setting and Data

1.1 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.

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 schoolchildren 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 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 set of social skills.

1.2 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 nation. The district has roughly 170,000 students enrolled in 180 schools, and is most known for its socioeconomic school integration program (Parcel and Taylor, 2015; Carlson et al., 2020), magnet schools (Dur et al., 2021), and year-round schools (McMullen and Rouse, 2012). Wake County mirrors the U.S. education landscape across a number of indicators. Perhaps most importantly, a greater 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 for just over four miles.[13]

Our sample draws from Wake County administrative data across four academic years (2014-15 to 2017-18) 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 who were in grades three to eight in the fall of 2014 in our full sample (See Appendix Table 1). This full set of students is described in Column 1 of Table 1.

In addition to the standard variables of sex and race/ethnicity, we construct indices of academic and behavioral achievement that we use as our main outcomes. We create an index for academic achievement from performance on state standardized test scores in math and

[13] See Appendix Figure 1 for more details on the district's transportation policy.

reading. We give these components equal weight, and standardize our measure of academic performance to have a mean of zero and a standard deviation of one for each year and grade. We create a behavioral index using factor analysis, relying on measures of absences, tardies, and short-term suspensions. Our behavioral index is also standardized to have a mean of zero and unit standard deviation, again for each year and grade. Riders and non-riders are more or less comparable on academic and behavioral measures. We present correlations between all outcomes in Appendix Tables 2 and 3.

In columns two and three of Table 1, we look at 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 about 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 all more likely to ride the bus than not. Interestingly, white students are significantly less likely to ride the bus to school. The consequences of racial differences in modes of transport to and from school are interesting questions for future research. Students who ride the bus tend to perform slightly worse (0.06 SD) than students who do not. These students are almost two times more likely to be absent from school and receive short term suspensions, but are less likely to be late to school.

In the two rightmost columns (4 and 5), we form two separate samples for use in our estimates. The ES-MS sample consists of students who began grades 3-5 in the fall of 2014 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 9,468 students in our ES-MS sample and 12,855 students in the MS-HS sample. We follow these students for four years (or for as many years as they are in our sample). These estimation samples largely mirror the broader ridership data in terms of demographics, though are slightly lower achieving.

We identify individual school buses and their riders by their unique arrival and departure times. 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.

On average, each student in our estimation sample has about five same-grade students meeting our sample requirements on the bus.[14] So that we base our estimates off of changes

[14]The number of students on each bus who share the same grade is likely undercounted, since we restrict our sample to students who ride the bus both to and from school, and ride the bus to both middle and

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. So that we can form a cardinal global ranking of bus effects across students, we need our sample to be comprised of connected sets.[15] To ensure that this condition is met, we require that the set of students an individual is exposed to on the bus changes with school switches before we estimate our models. Together, each estimation sample includes more than 6,000 sets of same-grade bus peers.

elementary school or middle and high school.

[15] See, for example, work on employer-employee match for an example of the importance of connected sets in similar estimation techniques (Abowd et al., 2008).

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	0.49	0.47	0.49	0.49
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Asian	0.09	0.10	0.07	0.11	0.10
	(0.28)	(0.30)	(0.26)	(0.31)	(0.30)
Black	0.22	0.22	0.20	0.19	0.22
	(0.41)	(0.42)	(0.40)	(0.39)	(0.41)
Hispanic	0.17	0.19	0.13	0.22	0.18
	(0.37)	(0.39)	(0.34)	(0.41)	(0.38)
White	0.49	0.45	0.56	0.44	0.46
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Other race	0.13	0.14	0.11	0.15	0.15
	(0.34)	(0.35)	(0.32)	(0.35)	(0.35)
English language learners	0.05	0.05	0.04	0.06	0.04
	(0.22)	(0.22)	(0.20)	(0.23)	(0.19)
Panel B: Achievement					
Math achievement	0.00	0.01	-0.01	-0.05	-0.07
	(1.00)	(1.01)	(0.98)	(1.02)	(1.02)
Reading achievement	-0.00	-0.02	0.04	-0.04	-0.06
	(1.00)	(1.01)	(0.98)	(1.01)	(1.02)
Achievement index	0.00	-0.02	0.04	-0.04	-0.12
	(1.00)	(1.01)	(0.98)	(1.01)	(1.05)
Absences	7.23	7.41	6.87	6.66	7.34
	(8.61)	(8.48)	(8.85)	(6.68)	(9.39)
Tardies	4.80	4.62	5.14	3.38	4.10
	(9.65)	(9.27)	(10.37)	(6.88)	(8.60)
Short-term suspensions	0.04	0.05	0.03	0.04	0.05
	(0.28)	(0.30)	(0.24)	(0.28)	(0.34)
Behavior index	0.00	-0.00	0.01	0.04	0.03
	(1.00)	(0.97)	(1.06)	(0.99)	(1.03)
Panel C: Bus Characteristics					
Bus ride duration (minutes)				36.34	37.98
				(26.86)	(26.91)
Same-grade bus-peers				4.91	5.71
				(3.15)	(3.65)
Observations	260,885	173,020	87,865	36,443	49,658
Students	81,128	48,744	32,384	9,468	12,855
Sets of same-grade bus-peers				6,091	6,759
Schools	184	182	182	136	59

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 1).

2 Empirical strategy

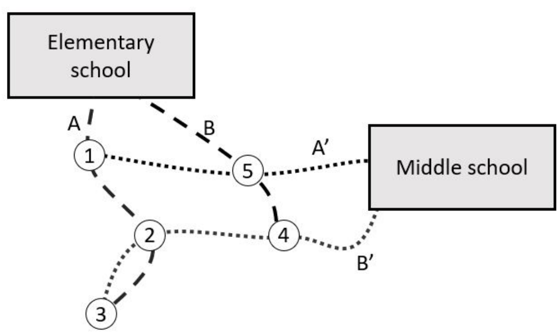
The aim of this paper is to study the role of informal social interactions on the development of academic and behavioral skills at different ages. For a clarification of the conceptual framework underlying our empirical approach, see Appendix.

The central empirical challenge comes from separating the bus effect from anything else correlated with which bus a student rides. For example, children of rich 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 that 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, and school 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.

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 the common residuals among riders of each bus.

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.

Given that we are able to recover unbiased estimates of individual effects, our identification fails if changes in the peer group riding a bus coincides with other time-varying 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-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.[16]

Formally, we extend variance-based approach to identifying peer effects (Glaeser et al., 1996; Graham, 2008) using techniques from the teacher value-added and firm-worker match literature (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.[17]

Our main outcomes are indices (Y_{ibsgt}) of academic and behavioral outcomes for all students each year, described in Section 1.

We decompose variation in student outcomes over time across various dimensions: bus (b), individual (i), school-pair (s), grade (g), and year (t).

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

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.[18] 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:

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

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 transitions from middle to high school, their bus will take a different route to school, and thereby contain a different set of students.

While the estimates of bus effects recovered by our covariance-based jackknife estimates, $\tilde{\mu}_{ib}$, are unbiased measures of the effects of bus b on outcome Y, we shrink them by their

[16]

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).

[17]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).

[18]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.

reliability to minimize mean squared prediction error since these are estimated with noise (Kane and Staiger, 2008; Chetty et al., 2014).[19] 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, 2020). We estimate the variance components by fitting the following mixed-effects model, where we adapt Equation 4 to include bus random effects:

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

$$\mu_b \sim N(0, \psi); e_{ig} \sim N(0, \theta)$$

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, we calculate the reliabilities of each bus effect as follows:

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

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

$$\tilde{\mu}_{ib} = \hat{\mu}_{ib}^{-i} \lambda_{Ab} \tag{5}$$

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 a standard deviation of one.

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

3 Results

3.1 Main results

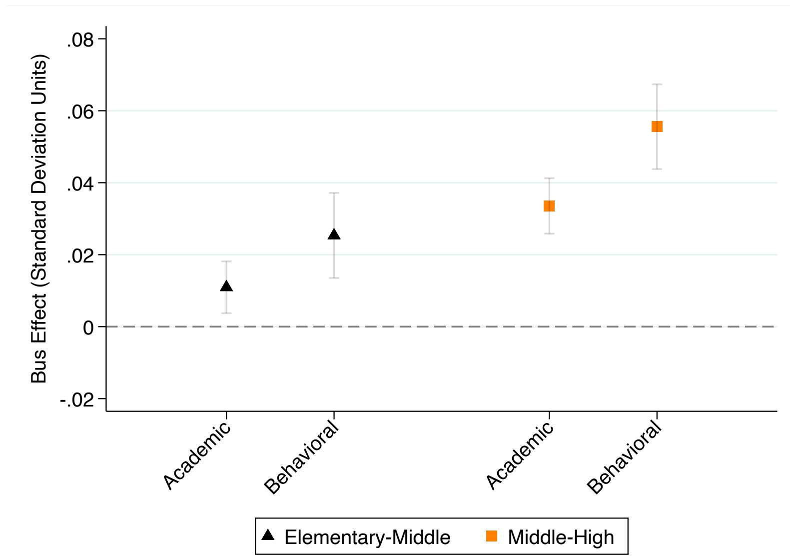
After recovering estimates of bus effects in academic and behavioral dimensions for both

[19] 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.

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 6. 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, $\tilde{\mu}$.

$$Y_{ibsgt} = \alpha_i + \beta\tilde{\mu}_{ib} + \phi_{s*} + \gamma_g + \delta_t + \epsilon_{ig} \tag{6}$$

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(s), grade, and year. Standard errors are clustered at the student level. From left to right the samples sizes of the above regressions are 32,374, 33,094, 39,735, and 39,961.

Figure 2 illustrates our main results (these results are also presented in Appendix Table 4). In our elementary and middle school sample we find that a one standard deviation shift in bus peers produces a 0.01 SD shift in a students' academic achievement and a 0.03 SD shift in a measure of their behavior. In our middle and high school sample we find that a one-standard deviation shift in bus peers results in a 0.04 SD and a 0.06 SD shift in academic achievement and behavior, respectively. Results in Appendix Table 4 suggest that the academic and behavioral effects of social interactions are distinct.

While these effects are relatively small in elementary and middle school, the effects for the middle and high school sample are similar in magnitude to teacher effects on academic achievement and behavior for students from North Carolina (Jackson, 2018). These magnitudes are also similar to those documented by Isphording and Zölitz (2020), who study business school classmates.

We validate these results following Card et al. (2018), and show how the residual in student performance—after accounting for student, school-pair, grade, and year fixed effects—compares for students who experience various magnitudes of shifts in their estimated bus effects in Appendix Figure 2. 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. Although these figures are demanding in terms of statistical power, they 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.

These results suggest two main takeaways. First, informal social interactions between students are likely to have greater effects on behavioral rather than academic outcomes. Second, these interactions appear to be larger in teenage years, which suggests that adolescent behavior is more malleable than foundational work on child development might suggest.

Next, we examine which components of our outcome indices may be driving our main estimates by regressing the main leave-out-student estimates on these components. Table 2 shows that the academic outcomes do not respond to the behavioral leave-out-student measures, and the behavioral outcomes do not respond to the academic leave-out-student measures, suggesting that social interactions among bus peers that affect academic achievement are distinct from those that affect behavior. We also find that the effects on academic achievement appear to be primarily driven by math rather reading performance. The effects on behavioral measures are driven primarily by absences and tardies rather than short-term suspensions.

Table 2: Drivers of main estimates

	Elementary-Middle		Middle-High	
	(1)	(2)	(3)	(4)
Achievement index	0.010	-0.001	0.034	0.012
	(0.004)	(0.003)	(0.004)	(0.004)
Math achievement (SD)	0.021	0.003		
	(0.004)	(0.004)		
Reading achievement (SD)	-0.002	-0.005		
	(0.004)	(0.004)		
Behavior index	-0.004	0.026	-0.002	0.054
	(0.005)	(0.006)	(0.005)	(0.006)
Absences	0.011	-0.224	0.024	-0.321
	(0.039)	(0.045)	(0.049)	(0.059)
Short-term suspensions	-0.001	0.000	-0.001	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Tardies	-0.022	-0.165	0.033	-0.821
	(0.045)	(0.058)	(0.075)	(0.083)
Observations	32,374	33,094	39,735	39,961

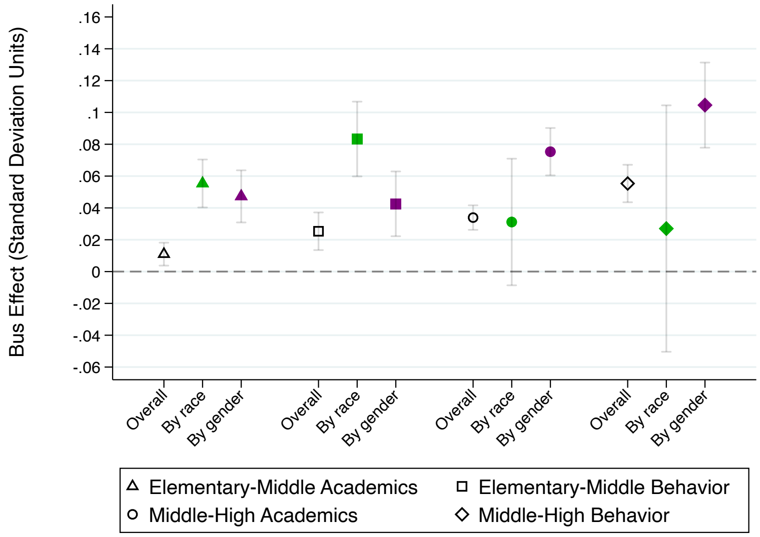
Notes: This figure plots the coefficients obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects. All regressions include fixed effects for individual, school(s), grade, and year. Columns 1 and 3 have leave-out-student estimates of 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.

3.2 Homophily by race and gender among bus peers

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 similar characteristics 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.

These results suggest that significant segregation by gender and race occurs among bus peers in elementary and middle school (See Figure 3). By high school, we find persistent segregation by gender but attenuated self-segregation by race.

Figure 3: 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 student level. From left to right the samples sizes of the above regressions are 32,374, 33,094, 39,735, and 39,961.

4 Discussion

We study how informal social interactions that take place outside of the classroom—namely on the school bus—affect student achievement and behavior. Methodologically, we show how recent ideas from recent value-added estimation of peer dynamics might extend to observational settings. Our results suggest that social interactions in informal settings may be important in shaping student learning outcomes, highlighting the need for research to better take into account the various out-of-school settings to which students are exposed.

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Appendix

Figures and tables

Figure 1: WCPSS 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." See Section 1 for detail on bus limits defined by policy and empirical bus counts in our analytic sample. The district's policy archive is available at https://www.wcpss.net/schoolboard.

Table 1: Grade-cohorts included in our estimation sample

	Elementary-Middle Sample				Middle-High Sample			
	2015	2016	2017	2018	2015	2016	2017	2018
Grade 3	x							
Grade 4	x	x						
Grade 5	X	X	X					
Grade 6		X	X	X	x			
Grade 7			x	x	x	x		
Grade 8				x	X	X	X	
Grade 9						X	X	X
Grade 10							x	x
Grade 11								x

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 X's) plus any observations for those same students that occur before and/or after a bus switch (lower-case x's). Within each estimation sample, students appear no more than four times (i.e., students are unique by grade-year within samples).

Table 2: Elementary-middle school sample outcome correlation matrix

	Academic Index	Math	Reading	Behavior Index	Absences	Suspensions	Tardies
Academic	1						
Math	0.93	1					
Reading	0.93	0.73	1				
Behavior	0.20	0.22	0.16	1			
Absences	-0.19	-0.20	-0.14	-0.86	1		
Suspensions	-0.13	-0.13	-0.12	-0.15	0.17	1	
Tardies	-0.13	-0.14	-0.10	-0.67	0.26	0.08	1

Notes: This table presents the correlation matrix between academic and behavioral outcomes for students in the elementary-middle school sample. The total number of student-by-year observations is 36,443.

Table 3: Middle-high school outcome correlation matrix

	Academic Index	Behavior Index	Absences	Suspensions	Tardies
Academic	1				
Behavior	0.42	1			
Absences	-0.37	-0.84	1		
Suspensions	-0.17	-0.21	0.17	1	
Tardies	-0.34	-0.69	0.28	0.13	1

Notes: This table presents the correlation matrix between academic and behavioral outcomes for students in the middle-high school sample. The total number of student by year observations is 49,658.

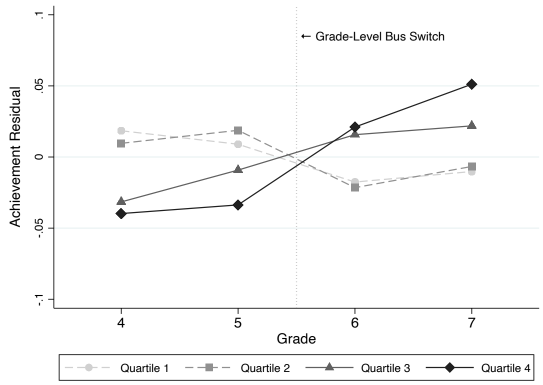
Table 4: Bus effects on academic and behavioral outcomes

	Academic Index			Behavior Index		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary-Middle Sample			
Bus-effect:						
Academic	0.011***		0.011***	-0.001		-0.009
	(0.004)		(0.004)	(0.006)		(0.006)
Behavior		0.002	-0.001		0.028***	0.030***
		(0.003)	(0.003)		(0.006)	(0.007)
			Panel B: Middle-High Sample			
Bus-effect:						
Academic	0.031***		0.031***	-0.001		0.031***
	(0.004)		(0.004)	(0.005)		(0.004)
Behavior		0.003	-0.002		0.047***	0.049***
		(0.004)	(0.004)		(0.006)	(0.007)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

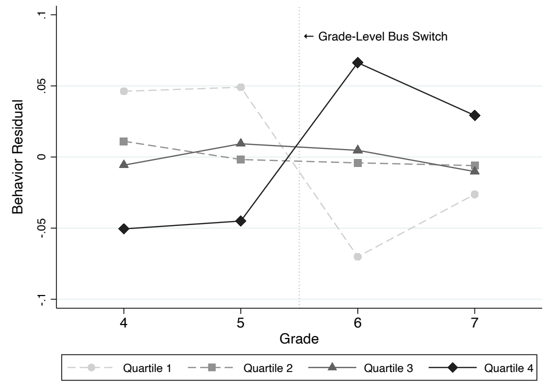
Notes: Panels A and B distinguish two separate analytic samples by grade-level pairs, as identification is based on student bus switching across grade levels. Sample sizes in Panel A range from 32,374 to 33,094. Sample sizes in Panel B range from 39,735 to 39,961. Each column includes two separate regressions 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 grade level pairs (elementary-middle school pairs in Panel A and middle-high school pairs in Panel B). Robust standard errors in parenthesis are clustered at the student level.

Figure 2: Validation of empirical strategy, following Card et al. (2018)

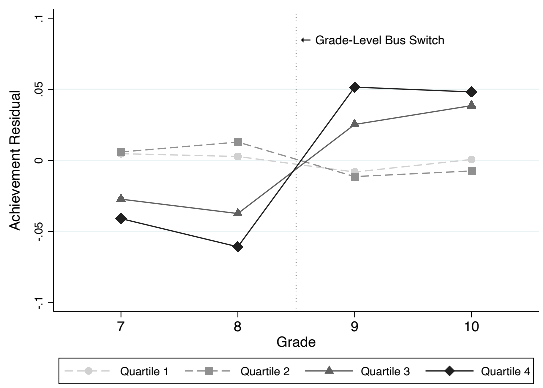
(a) Elementary-middle school academic achievement



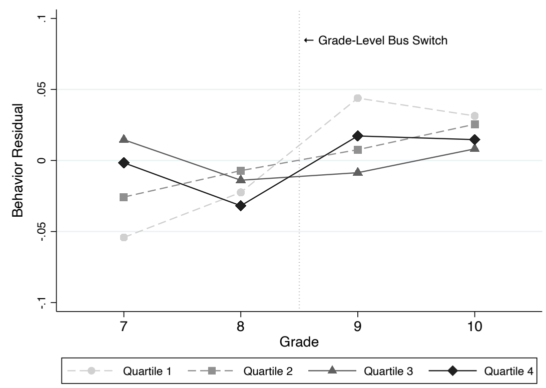
(b) Elementary-middle school behavior



(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-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 who 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 made up 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 made up of students who are in a relatively negative bus in their first school, and a relatively positive bus in their second school. By and large, these figures 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.

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.*[20] 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). 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 empirically.[21] Nonetheless, given that interactions on the bus take place through the repeated contact of a small group of students, effects of social interactions on the bus may stem primarily from endogenous interactions.[22]

Each bus has distinct social dynamics (ω_b) across academic and behavioral dimensions, $\omega_b = (\omega_A, \omega_B)$.[23] For example, academic achievement could be affected if it is (or is not) cool 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 try risky behaviors. We note that while these interactions might be instigated and dynamics formed by sharing the

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

[21] See De Giorgi et al. (2010) for a discussion of separately identifying exogenous and endogenous peer interactions.

[22] 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.

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

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.[24] The effects of bus b on student i are a function of social interactions on a bus (ω_b) and a students' 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, $\alpha_{ib} = v_i + \omega_{ib} + I_s$.[25]

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 $\beta = (\beta_A, \beta_B)^T$.

$$Y_{ib} = \alpha_{ib}^T \beta_s + \varepsilon_{ib} \equiv (v_i + \omega_{ib} + I_s)^T \begin{pmatrix} \beta_A \\ \beta_B \end{pmatrix} + \varepsilon_{ib} \tag{7}$$

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.

[24] 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.

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