Informal social interactions, behavior, and academic achievement: Evidence from bus-peers*

Matthew Lenard and Mikko Silliman, *Harvard University*

July 30, 2020

Abstract

We study the effects of informal social interactions on the development of academic and behavioral skills. We use idiosyncratic variation in peer groups stemming from changes in bus routes across elementary, middle, and high school to identify the effects of group dynamics on student outcomes, and estimate our model using a variance decomposition strategy. By leveraging two estimation samples—one consisting of students making the transition between elementary and middle school and the other of those making the transition between middle and high school—we are able to compare how the effects of informal social interactions vary across grades. In our elementary and middle school sample we find that a one standard-deviation increase in bus-peers increases academic performance by just over 0.01 SDs and behavior by 0.03 SDs. We find substantially higher estimates in our middle and high school sample, where a one standard deviation change in bus-peers corresponds to a 0.04 SD increase in academic performance and a 0.06 SD increase in behavior. While effects are smaller earlier in childhood, the effects of bus-peers approach the magnitude of teacher effects on academic and behavioral skills (Jackson, 2018). These findings suggest that student interactions outside the classroom—especially in adolesence—may be an important factor in the education production function.

*Matt Lenard - mlenard@g.harvard.edu; Mikko Silliman - silliman@g.harvard.edu. We are thankful to seminar participants at Harvard, Christopher Cleveland, Martti Kaila, Eric Taylor... for comments.

1 Introduction

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 these neighborhood effects (Deutscher, 2020), researchers across the social sciences still woirk 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) and overcoming the reflection problem (Manski, 1993a, 2000; Angrist, 2014). 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 is spent in the classroom, and classroom-based interactions take place in highly mediated environments not unique to granular neighborhood geographies, they are unlikely to explain much of the causal effects of place. Instead, repeated and informal interactions among smaller groups of students—whether in the cafeteria, during recess, or riding the bus—are likely to better resemble the types of interactions that take place in less mediated settings like neighborhoods.

By focusing on peer groups who ride the school-bus together, we seek to bridge neighborhood and school contexts in order to better understand how interactions among peers in informal settings contribute to the development of cognitive and non-cognitive skills. Bus-rides to and from school represent an interesting context for the study of social interactions because they are unstructured, constitute a period of time equivalent to roughy a class period, and are an unstudied component of the educational production function.[1]

The primary empirical challenge in identifying the effects of social interactions on school-buses is that ridership is not exogenously determined. Parents choose neighborhoods based primarily 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.

By focusing on school transitions and the idiosyncratic spatial structure of bus-routes, we develop a novel approach to estimating peer effects that takes advantage of transition in lieu of steady-state data.[2] As with the literature on teachers, our estimates are a measure of the extent to which student-level residuals correlate across bus-peers.[3] However, our context differs from that of teacher-led classrooms in at least one important way. In classroom contexts, the teacher contributes to student learning; on the bus, students themselves—as members of an informal, social group—largely contribute to their own outcomes.[4] As such, we develop a leave-out-student (jackknife) strategy where we estimate the effects of bus-peers for each student using data only from their peers. Once we construct these estimates for each student, we shrink our estimates using empirical Bayes and standardize them to have a mean of zero and unit standard deviation. We then regress student outcomes on our shrunken estimates to examine the effects of bus-peers on measures of academic

[1] One paper that does look at school buses is Austin et al. (2019), who look at how the exhaust fumes of school buses affect student health and achievement.

[2] In their review of empirical work on peer-effects, Durlauf and Ioannides (2010) suggest that "the use of transition versus steady-state data to infer social interaction effects should attract attention." Earlier work by

[3]

We follow the literature on non-experimental estimates of teacher value-added using variance decomposition, which finds that value-added measures from specifications that control for prior achievement and observable peer-characteristics show no signicant bias (Kane and Staiger, 2008; Chetty et al., 2014).

[4] 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 bad air on the bus - 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.

achievement and behavior. Our main estimates include an array of student, school-pair, year, and grade fixed effects and are robust to the exclusion of these controls.

To estimate our model, we use rich administrative data from Wake County, North Carolina, a large school system in which a majority of students ride the bus to and from school and over sixty percent of students experience group shifts among bus-peers in their grade-level as they transition between schools. We fit our models using two analytic samples. In the first, we estimate the effects of social interactions on the bus using students transitioning from elementary to middle school; in the second, we leverage the transition of students from middle to high school. This approach provides us with insight into the role of informal peer interactions in both childhood and adolesence.

While a student's neighborhood and initial bus may not be assigned at random, the change in bus-peers between the first and second bus (elementary to middle or middle to high) is as good as random. To test the validity of this identifying assumption, we show that the change in leave-out estimates between the two buses does not appear to be correlated with observable baseline student characteristics. Moreover, since we add student-level fixed effects to examine how changes in the leave-out estimates relate to changes in the student-levle residual, we do not believe our estimates to be driven by selection or reflection bias (Manski, 1993b; Angrist, 2014).[5]

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. Interestingly, we find that bus-peers that affect academic achievement have no effect on behavior, and bus-peers that affect behavior have no effect on achievement. As a point of reference, the effects for the middle and high school sample are similar to recent teacher effects on academic achievement and behavior Jackson (2018). Finally, we examine whether peer groups effects vary heterogeneously across gender and race. We find evidence suggesting significant self-segregation by gender and race among bus-peers in elementary and middle school. By high school, we find persistant self-segregation by gender but less self-segregation by race.

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 interactions appear larger in adolesence than in childhood. Third, our findings suggest that social interactions amongst bus-peers that affect academic achievement are distinct from those that affect behavior. Finally, we find that the effects on academic achievement appear to be primarily driven by math performance and behavioral measures are driven primarily by absences and tardies.

Our work extends the literature on peer effects in several ways. First, we introduce a new strategy to estimate peer effects, focusing on transitions between peer groups—an identification strategy that is potentailly applicable across a wide array of settings, including college transfer and employment changes. By studying 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, our strategy differs from those presented in recent work by Weidmann and Deming (2020) and Isphording and Zölitz (2020).

Second, our results suggest that social interactions in informal settings outside of school can have ramifi-

[5]While it is possible that our estimates are slightly attenuated by exclusion bias - the mechanical negative correlation between student outcomes and peer outcomes (Guryan et al., 2009; Fafchamps and Caeyers, 2020), our shrinkage of the leave-out estimates by their reliability should further minimize the extent of exclusion bias.

cations for what occurs within the classroom. While our focus is on the K-12 context, our results align with those found in studies of higher education where repeated interactions with peers can provide the foundation for friendships (Sacerdote, 2001; Zimmerman, 2003; Marmaros and Sacerdote, 2006; Camargo et al., 2010). 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 signicance 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 adolesence. While the mechanisms by which these effects are transmitted remain largely a unknown, new work has begun to extend these findings, and suggests that peers—especially adolescent peers—may play a role (Deutscher, 2020; Agostinelli et al., 2020). By providing a close look at a relatively unstudied form of peer interactions occuring at a granular geographic level, we show that informal interactions with a highly localized set of peers may indeed shape educational trajectories. Our results also reaffirm that these types of peer interactions may be particularly important in teenage years.

Third our results also contribute to a sparse literature describing factors that can shape the development of behavioral skills. As recent work has documented the growing important of social skills in the labor market (Deming, 2017; Edin et al., 2017), 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—even in later years—can affect behavioral skills (Jackson, 2018; Kraft, 2019). Our work contributes to this literature by demonstrating that social interactions also affect behavior, and that behavior may be malleable beyond childhood.

Our paper proceeds as follows. Section 2 describes the school bus as an informal social setting and summarizes our data sources. Section 3 outlines our empirical approach. Section 4 presents our results and Section 5concludes.

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. In our study, we overcome this trade-off by using rich 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 excercise discretion by assigning seats or moderating behavior, their influence over broad types of student interactions is likely a fraction of that excercised by either parents or classroom teachers.

Second, school bus ridership is widespread and consitutes 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. While data on school travel time is limited, recent work from the Urban Institute shows that time on public transporatation, 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 New York City, New Orleans, Washington DC, Denver, and Detriot, the median round-trip ride time was 40-62 minutes Blagg et al. (2018). Thus, the school bus represents a site where, like classrooms, social interactions are likely to occur. However, unlike classrooms, 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.

2.2 Institutional setting, data sources and outcomes

We examine the influence of informal social interactions on student outcomes in a large, representatative 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 170 schools, and is most known for its socioeconomic school integration program (Parcel and Taylor, 2015; Carlson et al., 2020), magnet schools (Dur et al., in progress), 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 36 minutes on round-trip bus travel and travels for just over four miles. The top quartile of riders spends at least 47 minutes over nearly six miles riding the bus and the longest round-trip ride in the district lasts 5 hours and covers 30 miles. While this extreme trip represents an outlier, it is not entirely surprising since the district's geographic footprint covers more than 800 square miles and takes roughly one hour to travel from the southern end to the northern tip. Although students who attend Title I or year-round schools have ride times comporable to their counterparts, students attending magnet schools (40% of total enrollment) ride for an additional 14 minutes.[6]

Our sample consists of data from four academic years (2014-2018) 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 all students who were in grades three to eight in the fall of 2014 in our full sample. In this full sample, white students are under-represented amongst riders and economically disadvantaged students are over-represented.

We construct indices of academic and behavioral achievement that we use as our main outcomes (Panel C, Table 1). We create an index for academic achievement from performance on state standardized test scores in math and 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. 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. Riders and non-riders are more or less comparable on academic and behavioral measures.

In the two rightmost columns (4 and 5), we form two separate samples for use in our estimates. The ES-MS sample consists of all students who began grades 3-5 in the fall of 2014 and the MS-HS sample

[6] The district sets a series of transportation goals designed to ensure student comfort and safety. Most students attending neighborhood schools are expected to ride the bus each way for no longer than one hour, while magnet students, who typically have longer routes, should ride for no longer than 1 hour, 45 minutes each way. The number of students permitted to ride per seat decreases by grade level. For example, elementary school students can sit 3 to a seat, which declines to 2.5 per seat at the middle school level and 2 to a seat for high schools.

consists of all students who began grades 6-8 that same fall. Each sample consists of roughly 35,000 students who we then follow for four years. These estimation samples by and large mirror the broader ridership data in terms of demographics and achievement.

Table 1: Descriptives

	Full sample (1)	Riders (2)	Non-riders (3)	ES-MS Sample (4)	MS-HS Sample (5)
Student characteristics					
			Panel A: Student Characteristics		
Male	0.51	0.51	0.50	0.51	0.51
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Asian	0.08	0.09	0.06	0.09	0.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	0.24	0.24	0.23	0.24	0.24
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hispanic	0.17	0.19	0.14	0.17	0.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
White	0.47	0.44	0.52	0.46	0.46
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Other race	0.12	0.13	0.11	0.13	0.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Students with disablities	0.14	0.13	0.16	0.14	0.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
English language learners	0.06	0.06	0.05	0.05	0.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Economically disadvantaged	0.35	0.37	0.30	0.36	0.35
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
			Panel B: Bus Characteristics		
Bus ride duration (minutes)		35.65		37.03	35.98
		(0.11)		(0.14)	(0.12)
Students per bus		13.39		12.40	13.66
		(0.05)		(0.06)	(0.06)
			Panel C: Achievement		
Math achievement (SD)	-0.02	-0.00	-0.06	-0.02	-0.03
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Reading achievement (SD)	-0.02	-0.03	0.00	-0.02	-0.02
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Achievement index	0.00	0.01	-0.01	-0.01	0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Absences	7.79	7.82	7.74	7.69	7.99
	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)
Tardies	5.12	4.97	5.42	4.22	5.63
	(0.04)	(0.04)	(0.07)	(0.04)	(0.04)
Short-term suspensions	0.07	0.07	0.07	0.08	0.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Behavior index	-0.01	0.00	-0.04	-0.03	-0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Observations	83,085	55,230	27,855	33,683	35,108

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

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

3 Approach

3.1 Framework

The aim of this paper is to study the role of informal social interactions on the development of academic and behavioral skills over time. 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, 1993a; Blume et al., 2015; Bursztyn et al., 2019). 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 (1993a) differentiates between two different types of social interactions: *contextual* and *endogenous* (see Blume et al. (2015) for a more recent discussion). In the first, the personal characteristics of others—for example, classroom disruptions (as studied by Carrell and Hoekstra (2010))—affect one's own behavior. In contrast, in endogenous interactions, the behavior of individuals in a group is simultaneously determined through social dynaimcs—potentially stemming from social pressure, conformity, or group norms, as studied by Bursztyn and Jensen (2015).

In our context, students are exposed to other students when they ride the bus (b) to and from school.

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. As such, we consider any peer effects exhibited on the bus to stem from primarily endogenous interactions.

Each bus has distinct social dynamics (ω_b) across academic and behavioral dimensions, $\omega_b = (\omega_A, \omega_B)$. 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 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.[7] The effects of bus b on student i are a function of the group dynamics on a bus (ω_b) and a students' responsiveness (D_i) to these dynamics, 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, the dynamics on the bus, and other factors including, for example, school inputs, $\alpha_{ib} = v_i + \omega_{ib} + I_s$.

Skills (Y_i) are observed, with error (ε_{ib}), through items such as suspensions or grades. The extent to which any observable measure of student skills is shaped by bus dynamics is represented by $\beta = (\beta_A, \beta_B)$.

$$Y_{ib} = \alpha_{ib}\beta_s + \varepsilon_{ib} \equiv (v_i + \omega_{ib} + I_s) \begin{pmatrix} \beta_{Ab} \\ \beta_{Bb} \end{pmatrix} + \varepsilon_{ib} \tag{1}$$

We consider what we call "bus-effects" (μ_b) to be the mean effect of social dynamics on bus b on skill Y, $\mu_b = E[\omega_{ib}\beta_b]$.

Standardizing μ_b 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.

3.2 Identification

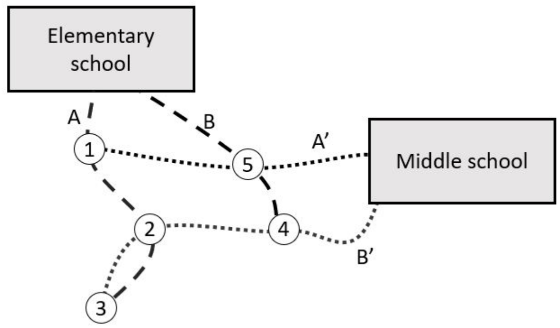
The central empirical challenge comes from separating the bus-effect from other things correlated with which bus a student rides. For example, children of rich or poor families are likely to cluster together on buses—making it difficult to separate systematic differences in achievement stemming from 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. This variation 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. In turn, this will allow us to estimate group dynamics.

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, with the same students riding 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.

[7] 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.

Figure 1: Visual representation of idea



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, since families do move in search of better schools for their children, and these moves do can coincide with school changes. However, to shield our estimates from this type of threat, we include a school-pair fixed effect in our estimating equations. This fixed effect is intended to absorb variation in outcomes associated with family preferences for schools that deviate from the typical school transition.

Formally, we combine this exogenous variation stemming from changes in bus routes and a variance-based approach to identifying peer effects (Glaeser et al., 1996; Graham, 2008), extending these approaches using techniques from the teacher value added and firm-work match literature (Abowd et al., 2008; Kane and Staiger, 2008; Chetty et al., 2014; Jackson, 2018).

In our main estimates we define groups of bus-peers as the set of students from the same grade who ride a bus to and from school together.[8] We build these groups based on ridership data from the year directly before or after a school transition. For example, in the elementary-middle school sample, the bus a student rides in fifth grade (the last year of elementary school in North Carolina) will be assigned to them for the entirety of their elementary school tenure, and the bus a student rides in sixth grade will be assigned to them for the entirety of their middle school tenure. 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 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.[9] 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.

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

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

[8]Our identification of bus ID's in the data is requires students ride the bus in both directions. As a result, we are not able to use students who ride the bus in only one direction in our estimation.

[9]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.

$$Y_{ibsgt} = \alpha_i + \mu_b + \phi_{s*} + \gamma_g + \delta_t + \epsilon_{ig} \tag{2}$$

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. 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:

$$\tilde{\mu}_{ib} = \hat{\mu}_{ib}^{-i} \tag{3}$$

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 comes 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 reliability to minimize mean squared prediction error since these are estimated with noise (Kane and Staiger, 2008; Chetty et al., 2014). 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, 2019). We estimate the variance components by fitting the following mixed-effects model, where we adapt Equation 4 to include bus random effects:

$$Y_{ibsgt} = \alpha_i + \mu_b + \phi_{s*} + \gamma_g + \delta_t + \epsilon_{ig} \tag{4}$$

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

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:

$$\lambda_b = \frac{\hat{\sigma}_\mu^2}{\hat{\sigma}_\mu^2 + \frac{\hat{\sigma}_\epsilon^2}{n_b}}. \tag{5}$$

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

$$\tilde{\mu}_{ib} = \hat{\mu}_{ib}^{-i} \lambda_{Ab} \tag{6}$$

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.

3.3 Validity

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).[10]

We test this assumption by comparing the "pre-treatment" characteristics of students who ride a similar buses with similar bus effects in their first school, but who ride buses with different bus effects in their subsequent school. This test is meant to ensure that the instruments we use to capture bus dynamics are orthogonal to a student's own baseline characteristics.

To do this, we limit our sample to students the first time we observe them in our data and examine how the change in bus peer quality as measured by the difference in shrunken jackknife estimates ($\Delta\tilde{\mu}_{ib}^{ESMS}$ or $\Delta\tilde{\mu}_{ib}^{MSHS}$) is associated with observable background characteristics, controlling for their initial bus, school, and year (Equations 7 and 8).

$$X_{ibsgt} = \beta_1 \Delta\tilde{\mu}_{ib}^{ESMS} + \pi_b^{ES} + \phi_{s*} + \delta_t + \epsilon_i \tag{7}$$

$$X_{ibsgt} = \beta_1 \Delta\tilde{\mu}_{ib}^{MSHS} + \pi_b^{MS} + \phi_{s*} + \delta_t + \epsilon_i \tag{8}$$

If our assumptions are met, β_1 should be indistinguishable from zero. While this balance check produces a handful of statistically significant estimates, all coefficients are close to zero. Moreover, the largest and most statistically significant coefficient produced through this balance check—the coefficient for "male" for the middle and high school behavior jackknives—may in fact affirm the validity of our approach. Males are more likely to be held back in the transition between middle and high school for behavior, which may result in a mechanical reduction in male students in high school buses—potentially explaining this imbalance in peer dynamics. Still, by including individual fixed effects, our main estimation strategy is significantly more conservative than these approach we use to assess balance in observables.

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 9. 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 $\tilde{\mu}$.

$$Y_{ibsgt} = \alpha_i + \beta\tilde{\mu}_{ib} + \phi_{s*} + \gamma_g + \delta_t + \epsilon_{ig} \tag{9}$$

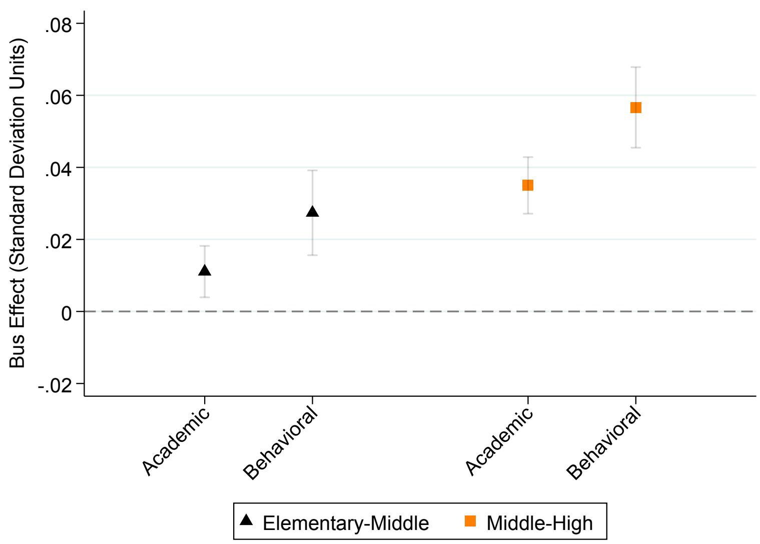
[10] While it is possible that our estimates are attenuated by exclusion bias - the mechanical negative relationship between an individual's outcome and the leave-out-mean of that outcome (Guryan et al., 2009; Angrist, 2014; Fafchamps and Caeyers, 2020) - our empirical Bayes procedure should help to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

Table 4: Balance in observable characteristics

	Elementary-Middle		Middle-High	
	(1)	(2)	(3)	(4)
Male	0.009	0.011	0.036***	0.007
	(0.011)	(0.009)	(0.008)	(0.008)
Asian	-0.003	0.002	0.002	0.003
	(0.005)	(0.004)	(0.004)	(0.004)
Black	0.015**	0.011**	-0.011**	-0.008
	(0.006)	(0.005)	(0.005)	(0.006)
Hispanic	-0.007	-0.006	0.003	0.014***
	(0.007)	(0.006)	(0.005)	(0.005)
White	-0.012	-0.004	0.004	-0.010*
	(0.007)	(0.007)	(0.006)	(0.006)
Other race	0.004	-0.000	0.005	0.004
	(0.006)	(0.005)	(0.005)	(0.005)
English language learners	-0.013**	-0.004	-0.001	-0.003
	(0.006)	(0.005)	(0.003)	(0.003)
Economically disadvantaged	0.003	-0.005	-0.002	-0.005
	(0.006)	(0.005)	(0.005)	(0.005)
Observations	6222	6348	8907	8957

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

Figure 2: Main estimates: Bus-peers, academic achievement, and behavioral outcomes



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. From left to right the samples sizes of the above regressions are 32,507, 33,257, 39,919, and 40,130.

Figure 2 illustrates our main results. In our elementary and middle school sample we find that a one standard deviation shift in bus-peers produces in 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. To provide a reference point for these magnitude, we point to the teacher value added literature. While these effects are relatively smaller in elementary and middle school, the effects for the middle and high school sample are similiar in magnitude to teacher effects on academic achievement and behavior for students from North Carolina Jackson (2018).

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 than in elementary school, which suggests that adolescent behavior is more malleable than foundational work on early 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. 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 amongst 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 5: What's driving the main estimates?

	Elementary-Middle		Middle-High	
	(1)	(2)	(3)	(4)
Achievement index	0.010***	-0.002	0.036***	0.007*
	(0.004)	(0.003)	(0.004)	(0.004)
Math achievement (SD)	0.021***	0.002	-	-
	(0.004)	(0.004)	-	-
Reading achievement (SD)	-0.001	-0.006	-	-
	(0.004)	(0.004)	-	-
Behavior index	-0.002	0.028***	0.001	0.055***
	(0.005)	(0.006)	(0.005)	(0.006)
Absences	0.014	-0.233***	0.030	-0.333***
	(0.040)	(0.045)	(0.051)	(0.060)
Short-term suspensions	-0.000	0.000	0.000	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Tardies	-0.028	-0.182***	0.024	-0.841***
	(0.046)	(0.061)	(0.077)	(0.084)
Observations	32507	33237	39919	40130

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

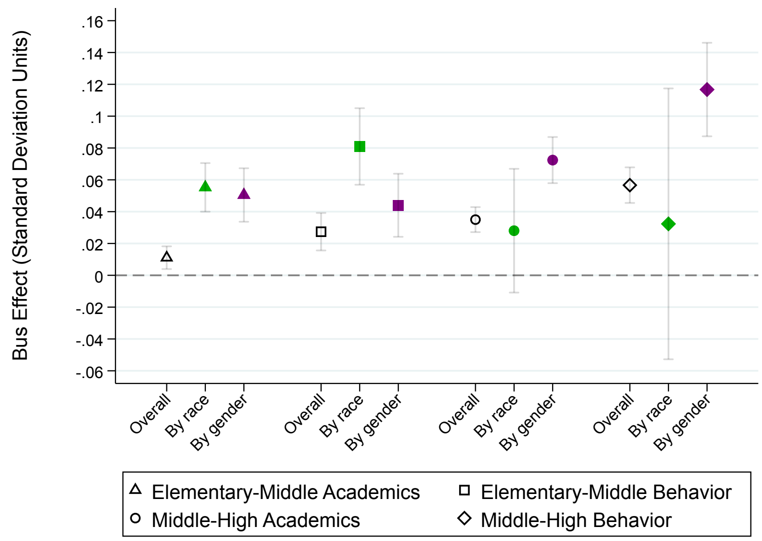
Notes: This figure plots the coefficients obtained from regressing student outcomes (academic achievement and behavior) on leave-out-student estimates of bus effects. All regressions include fixed effects for individual, school(s), grade, and year. Columns 1 and 3 have leave-out-student estimates of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

4.2 Homophily by race and gender amongst 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 dimensions of race and gender prior to fitting our models.

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

Figure 3: Peer dynamics on the bus: Overall, gender, and race



5 Discussion

In this paper, we introduce a new approach to estimating the effects of informal social interactions on student outcomes by drawing from the peer effects and teacher value added literatures. By estimating a "bus effect" and regressing student outcomes on leave-one-out measures of peer quality, we show that changes in informal social interactions significantly affect individual academic and behavioral outcomes in magntudes that, especially among adolescents, are comporable to teacher effects.

Our findings have a number of implications. First, we introduce a new strategy to estimate the effects of informal social interactions by borrowing from the peer effects and teacher value added literatures. While bus ridership is not randomly assigned, we leverage the arguably exogenous variation generated from changes in bus routes across individuals. Our approach is potentially applicable to additional settings, such as college transfer and job switching. Second, our results suggest that social interactions in informal settings outside of school can have ramifications for what occurs within the classroom. In particular, we shed light on the potential channels through which granular levels of place matters, such as the observation that neighborhood may be particularly important in adolesence as indicated by our substantially larger bus effects among older students. Finally, our results contribute to a sparse literature describing factors that can shape the development of behavioral skills. Our work contributes to this literature on social skill development by demonstrating that social interactions also affect behavior, and that behavior may be malleable beyond childhood.

References

Abowd, J. M., Kramarz, F., and Woodcock, S. (2008). Econometric analyses of linked employer–employee data. In *The econometrics of panel data*, pages 727–760. Springer.

Agostinelli, F., Doepke, M., Sorrenti, G., and Zilibotti, F. (2020). It takes a village: the economics of parenting with neighborhood and peer effects. Technical report, National Bureau of Economic Research.

Angrist, J. D. (2014). The perils of peer effects. *Labour Economics*, 30:98–108.

Austin, W., Heutel, G., and Kreisman, D. (2019). School bus emissions, student health and academic performance. *Economics of Education Review*, 70:109–126.

Blagg, K., Chingos, M., Corcoran, S. P., Cordes, S. A., Cowen, J., Denice, P., Gross, B., Lincove, J. A., Sattin-Bajaj, C., Schwartz, A. E., et al. (2018). The road to school: How far students travel to school in the choice-rich cities of denver, detroit, new orleans, new york city, and washington, dc. *Urban Institute Student Transportation Working Group, https://www. urban. org/sites/default/files/publication/97151/the_road_to_school_6. pdf.*

Blume, L. E., Brock, W. A., Durlauf, S. N., and Jayaraman, R. (2015). Linear social interactions models. *Journal of Political Economy*, 123(2):444–496.

Bursztyn, L., Egorov, G., and Jensen, R. (2019). Cool to be smart or smart to be cool? understanding peer pressure in education. *The Review of Economic Studies*, 86(4):1487–1526.

Bursztyn, L. and Jensen, R. (2015). How does peer pressure affect educational investments? *The Quarterly Journal of Economics*, 130(3):1329–1367.

Camargo, B., Stinebrickner, R., and Stinebrickner, T. (2010). Interracial friendships in college. *Journal of Labor Economics*, 28(4):861–892.

Carlson, D., Bell, E., Lenard, M. A., Cowen, J. M., and McEachin, A. (2020). Socioeconomic-based school assignment policy and racial segregation levels: Evidence from the wake county public school system. *American Educational Research Journal*, 57(1):258–304.

Carrell, S. E., Hoekstra, M., and Kuka, E. (2018). The long-run effects of disruptive peers. *American Economic Review*, 108(11):3377–3415.

Carrell, S. E. and Hoekstra, M. L. (2010). Externalities in the classroom: How children exposed to domestic violence affect everyone's kids. *American Economic Journal: Applied Economics*, 2(1):211–28.

Chetty, R., Friedman, J. N., and Rockoff, J. E. (2014). Measuring the impacts of teachers i: Evaluating bias in teacher value-added estimates. *American Economic Review*, 104(9):2593–2632.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment. *American Economic Review*, 106(4):855–902.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2):31–47.

Deming, D. (2009). Early childhood intervention and life-cycle skill development: Evidence from head start. *American Economic Journal: Applied Economics*, 1(3):111–34.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640.

Deutscher, N. (2020). Place, peers, and the teenage years: Long-run neighborhood effects in australia. *American Economic Journal: Applied Economics*, 12(2):220–49.

Durlauf, S. N. and Ioannides, Y. M. (2010). Social interactions. *Annu. Rev. Econ.*, 2(1):451–478.

Edin, P.-A., Fredriksson, P., Nybom, M., and Ockert, B. (2017). The rising return to non-cognitive skill.

Fafchamps, M. and Caeyers, B. (2020). Exclusion bias and the estimation of peer effects. *NBER Working Paper No. 22565*.

Glaeser, E. L., Sacerdote, B., and Scheinkman, J. A. (1996). Crime and social interactions. *The Quarterly Journal of Economics*, 111(2):507–548.

Graham, B. S. (2008). Identifying social interactions through conditional variance restrictions. *Econometrica*, 76(3):643–660.

Guryan, J., Kroft, K., and Notowidigdo, M. J. (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics*, 1(4):34–68.

Heckman, J., Pinto, R., and Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, 103(6):2052–86.

Isphording, I. E. and Zölitz, U. (2020). The Value of a Peer. *SSRN Electronic Journal*.

Jackson, C. K. (2018). What do test scores miss? the importance of teacher effects on non–test score outcomes. *Journal of Political Economy*, 126(5):2072–2107.

Jackson, C. K., Porter, S. C., Easton, J. Q., Blanchard, A., and Kiguel, S. (2020). School effects on socio-emotional development, school-based arrests, and educational attainment. Technical report, National Bureau of Economic Research.

Kane, T. J. and Staiger, D. O. (2008). Estimating teacher impacts on student achievement: An experimental evaluation. Technical report, National Bureau of Economic Research.

Kraft, M. A. (2019). Teacher effects on complex cognitive skills and social-emotional competencies. *Journal of Human Resources*, 54(1):1–36.

Manski, C. F. (1993a). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542.

Manski, C. F. (1993b). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, 60(3):531.

Manski, C. F. (2000). Economic analysis of social interactions. *Journal of economic perspectives*, 14(3):115–136.

Marmaros, D. and Sacerdote, B. (2006). How do friendships form? *The Quarterly Journal of Economics*, 121(1):79–119.

McMullen, S. C. and Rouse, K. E. (2012). School crowding, year-round schooling, and mobile classroom use: Evidence from north carolina. *Economics of Education Review*, 31(5):812–823.

Mulhern, C. (2019). Beyond teachers: Estimating individual guidance counselors effects on educational attainment.

Parcel, T. L. and Taylor, A. J. (2015). *The end of consensus: Diversity, neighborhoods, and the politics of public school assignments*. UNC Press Books.

Sacerdote, B. (2001). Peer effects with random assignment: Results for dartmouth roommates. *The Quarterly journal of economics*, 116(2):681–704.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far? In *Handbook of the Economics of Education*, volume 3, pages 249–277. Elsevier.

Weidmann, B. and Deming, D. (2020). Team players: How social skills improve group performance. *NBER Working Paper Series 27071*.

Zimmerman, D. J. (2003). Peer effects in academic outcomes: Evidence from a natural experiment. *Review of Economics and statistics*, 85(1):9–23.

Appendix

Table 1: Correlations in peer dynamics for various outcomes: Elementary and middle school sample

	Academic Index	Math	Reading	Behavior Index	Absences	Suspensions	Tardies
Academic	1						
Math	0.88	1					
Reading	0.85	0.52	1				
Behavior	0.27	0.23	0.23	1			
Absences	-0.16	-0.15	-0.13	-0.58	1		
Suspensions	-0.40	-0.41	-0.31	-0.36	0.15	1	
Tardies	-0.18	-0.15	-0.16	-0.83	0.14	0.35	1

Table 2: Correlations in peer dynamics for various outcomes: Middle and high school sample

	Academic Index	Behavior Index	Absences	Suspensions	Tardies
Academic	1				
Behavior	0.07	1			
Absences	-0.12	-0.69	1		
Suspensions	0.11	0.02	0.05	1	
Tardies	-0.14	-0.81	0.26	-0.23	1