How Socioeconomic and Parental Background Shape Peer Networks and Educational Spillovers*

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Abstract

This paper examines how socioeconomic background and student characteristics influence friendship formation and educational outcomes. We take advantage of the combination of survey data combined with a rich set of registry data to observe both student friendships and detailed information on parental and socioeconomic backgrounds. We find significant effects of parental background—specifically age, ethnic background, and social security status—on student friendship formation. Parental income also plays a role, though we find no significant effects of parental wealth. The strongest determinants of friendship formation are shared gender and class membership, along with evidence of assortative matching based on academic skills. To estimate peer effects, we instrument for friends' academic performance using pre-existing skill measures. Our results indicate substantial spillovers: a one-standard-deviation increase in friends' GPA leads to approximately a 0.62 standard deviation increase in a student's own GPA. We leverage these findings to assess how classroom structure shapes academic outcomes through its influence on student friendships. We demonstrate that the realized social network significantly impacts individual achievement, suggesting that policies targeting peer interactions could be an effective tool for improving student outcomes.

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1 Introduction

Peer effects in education have long been documented in the literature, especially for particular subgroups of the population (Sacerdote, 2011). Students' academic outcomes are not only shaped by their own abilities and family backgrounds, but also by the broader social environment in which learning takes place. As a result, policy interventions often aim to harness peer influences in ways that raise overall educational performance. However, these efforts can be undermined if the interventions themselves inadvertently reshape the underlying social networks, reducing or even reversing the desired effects (Carrell, Sacerdote, and West, 2013). This possibility highlights the importance of examining both how friendships form and how they translate into academic spillovers. To address this, we merge survey data with comprehensive registry data, enabling us to capture detailed information on student backgrounds and outcomes with the specific networks in which the students interact. Our analysis focuses on how parental background, student skills, and classroom composition influence student outcomes, thereby providing insights into the interaction between social relationships and academic performance.

In this paper, we use a unique dataset to estimate both network formation and peer effects in two Norwegian middle schools. Our results point to substantial peer effects, accompanied by significant homophily and degree heterogeneity within student friendship networks, meaning there is a large variation in the number of friends between students. The magnitude of the peer effects suggests that modifying the composition of student friendship networks could serve as a cost-effective policy tool for improving academic outcomes. Given that classroom assignment strongly determines friendship formation, we focus on how reallocating students across classrooms impacts both network structure and student performance. We also explore methods for identifying the optimal network—defined as the configuration of friendships that maximizes average learning in the sample. Our analysis therefore provides insights into the broader implications of such interventions, not only for average student outcomes but also for variance in outcomes in the student population.

Our sample offers several advantages for analyzing spillovers associated with parental background. The two public schools in our study assign students largely based on geographic catchment areas.[1] This setup provides us with substantial variation in parental backgrounds within each school, spanning students from highly educated, affluent families to students from households relying on government assistance. By integrating survey responses with registry data, we accurately capture friendship links, parental background, and student outcomes, enabling a detailed analysis of how network structures shape academic performance.

Our network formation model is based on the model of Graham (2017), where links are formed between students if the total surplus of the link is positive. The surplus is modeled as containing three main components. The first is the sum of link specific covariates, such as both students

[1] Norwegian elementary schools assign students based on residential address, with transitions from primary to middle school following predefined geographic zones. While students may apply for transfers outside their designated middle school, such instances are uncommon and usually require specific justifications, such as specialized academic programs, bullying or logistical considerations. Consequently, school composition closely reflects neighborhood demographics.

being in the same class. The second is the sum of individual popularity of the two students, modeled as fixed effects. The last component is a link-specific shock, assumed to follow a logistical distribution. Including these popularity terms substantially improves the model's fit and produces realistic friendship networks in our simulations.

To estimate the spillovers in peer effects in GPA in our sample, we use the Linear-in-Mean model as developed in Manski (1993). Identification of the endogenous peer effect, meaning the coefficient on peer average outcomes, is dependent on an exogenous peer covariate that is used as an instrument (Bramoullé, Djebbari, and Fortin, 2009). Specifically, we use the score from the national test the students took in fifth grade. This score is arguably exogenous to idiosyncratic shocks to GPA in middle school, which is starts two years later. Despite the long time between our sample period and this national test, we find that the instrument is valid, with peers average national test scores strongly predicting their average GPA. This means our model has a solid first stage, allowing us to reliably estimate the spillovers in our data.

Based on our survey, we find that students generally lack awareness of their friends' parental background.[2] Nevertheless, these networks exhibit strong homophily, with students more likely to befriend peers whose parents share similar socioeconomic traits. This pattern persists even after controlling for geographic proximity, including both the walking distance between students' homes, whether the students attended the same elementary school, and their pre-existing skills before entering middle school. Overall, our results indicate that friendship formation is predominantly driven by shared environments—most notably classroom assignment and gender—while parental background and broader socioeconomic factors only modestly affect the network formation. As such, our results expand on previous results in the literature on friendship formation in educational settings (An, 2022; De Paula, 2020; Mayer and Puller, 2008), which lack our detailed knowledge about the parents of the students.

We also uncover a substantial GPA spillover effect, which is large compared to other recent research (Bramoullé, Djebbari, and Fortin, 2020). In our analysis we find that a one-standard-deviation average increase in friends' GPA is associated with an approximate 0.62 standard deviation increase in a student's own GPA. Though the peer effects appear to be stronger among male and high-achieving students, these subgroup differences are generally not statistically significant. However, the large observed heterogeneities align well with previous findings in the literature (e.g., Han and Li, 2009; Michelman, Price, and Zimmerman, 2022; Sacerdote, 2001), emphasizing the importance of classroom composition in shaping both networks and academic outcomes.

Our first contribution is the construction of a uniquely detailed dataset that integrates student survey responses with comprehensive registry data. This combination allows us to precisely measure friendship networks and capture rich information on students and their parents, including socioeconomic status, education level, and other relevant background characteristics. By mapping out both the social ties and the demographic traits of students and their families, this dataset

[2] As part of the survey, students were asked about their friends parents characteristics, suchh as general education level. Over 90% of the responses were "I don't know".

provides us with a platform to investigate both the network formation and peer effects.

Our second contribution is to examine how parental background and student characteristics jointly shape friendship formation and learning spillovers. To identify peer spillovers in GPA, we instrument friends' outcomes using their average national test scores from fifth grade in reading, arithmetic, and English. These test scores were measured two years prior to the start of middle school, and they offer a plausibly exogenous measure of peers' academic ability that predates the formation of the middle school friendship networks. Under the assumption that friends' prior test scores are uncorrelated with current, student-specific shocks to GPA—conditional on the student's own prior test score—we identify the the peer effect. Our approach therefore contributes to the literature on educational peer effects by estimating how various student, parental, and peer characteristics interact to influence academic performance.

Our third contribution examines how network structure influences aggregate student performance through estimated peer effects. By leveraging our network formation model, we simulate counterfactual friendship networks that align with students' observed preferences. Using these simulated networks, we then estimate counterfactual academic outcomes based on our peer effects model. Our findings reveal that small changes in the network structure can lead to substantial impacts on the distribution of student achievement. This simulation exercise is highlighting the potential for targeted interventions that optimize classroom composition to enhance the overall academic performance of students, and the analysis closely relates to previous research on improving student outcomes, such as optimizing teacher-student matching (Jackson, Rockoff, and Staiger, 2014; Rockoff, 2004). Our findings suggest that interventions targeting network structures could provide a cost-effective alternative to these approaches, potentially yielding comparable improvements in academic performance.

The paper is structured as follows: Section 2 outlines the institutional setting. Section 3 describes the dataset and presents key descriptive statistics. Section 4 details our identification strategy, while Section 5 presents the empirical findings. In Section 6, we explore the implications of our results for class assignment policies. Finally, Section 7 discusses our findings and provides concluding remarks.

2 Institutional Setting

Norway's compulsory education system spans ten years, catering to students aged 6 to 16. It is divided into two main stages: a seven-year primary school phase (grades 1–7) and a three-year lower secondary school phase (grades 8–10). Most students attend local public schools, which are administered by local municipalities and are free of charge. Only about 4 % of students are enrolled in private schools. Both public and most private institutions follow a national curriculum and operate under a shared legal framework, ensuring a comparable education for most students across the country. Schools that wish to implement alternative curricula must obtain an approval from national authorities.

Public schools typically follow a neighborhood rule, with catchment areas determined by local governments, and the education system is comprehensive, with no tracking or grade promotion and retention practices. In primary school, the focus is on developing foundational skills in subjects such as Norwegian, mathematics, English, science, social studies, arts, and physical education, and in lower secondary school the curriculum expands by offering elective subjects that align with the students' academic interests and academic goals.

The national curriculum emphasizes cross-disciplinary skills, including oral and written expression, reading, mathematics, and digital literacy. A variety of assessment methods—such as exams, projects, presentations, and classroom evaluations—are employed to evaluate students' knowledge and abilities. In 2008, the curriculum was enhanced to define specific competencies students should acquire at different levels, reinforcing grades as criterion-referenced measures (Tveit, 2014). This approach aims to ensure that grades are fair, accurately reflect students' abilities, and align with the educational objectives set forth by the national curriculum.

2.1 Participating schools

The two middle schools involved in the project were both built in the early 1960s and are well established. Each school serves around 300 students, with four classes across the three middle school grades in both of the schools. Both schools have also adopted modern approaches to student engagement and extracurricular activities.

One school emphasizes daily physical activity, encouraging students to actively participate in the choice of activities. This approach fosters physical well-being and promotes a sense of personal agency and involvement in shaping their school experience. The second school offers traditional sports facilities such as a swimming pool, football, basketball, and handball courts, but it also integrates modern options like a parkour course and a fully equipped gaming room. These facilities reflect the school's aim to provide both physical and digital environments for student development.

Together these schools are representative of modern middle schools—one focused on student-driven physical engagement, the other offering a broad array of physical and digital spaces for learning and recreation. Both schools also primarily recruit from a total of five nearby primary schools, but have drawn students from a total of 42 elementary schools within the cohorts studied in this paper.

3 Data

In this project, we utilize data from multiple sources. The central component of our dataset was collected through a survey that gathered detailed information on student friendships from two lower secondary schools. By linking these survey responses to Norwegian full-population registry data, we created a rich dataset that allows us to explore not only the existence of friendships but also their depth and quality, as well as other social factors that contribute to the generation of friendships and in turn educational outcomes.

3.1 The Student Survey

In the student survey, we mapped all friendships at the participating schools, who serves students in grades 8 through 10. These schools were selected based on their size, demographic characteristics, but also willingness to participate in the research. At both schools, every student was asked to complete the survey, which included lists of all students in every class. Participants were instructed to identify anyone they considered a friend, with no limit on the number of nominations. This open-ended approach enabled students to report their social connections freely, providing a full overview of their social network at the school.

For the purposes of this study, we primarily define a friendship as a reciprocal relationship between two students, where both students mutually nominated each other as friends in the survey. This operationalization reduces the likelihood of including unilateral perceptions of friendship, which may not reflect actual social influence. By focusing on confirmed mutual relationships, we aim to more accurately map the social networks that could affect academic performance.

In addition to charting friendships, the survey gathered information on students' social activities outside of school, homework habits, and the friends with whom they engaged in these activities. It also collected background details, such as extracurricular activities, academic performance, and family circumstances. To understand the depth and closeness of friendships, students were asked questions about their friends and their friends' parents. Residential addresses were also recorded, to calculate walking distances to school and between students' homes. This information helps us understand various factors influencing network formation.

A key goal of the survey was to maximize participation, thereby reducing non-response bias. Across both schools, 94% of students completed the survey. Only one student was restricted from participating by their parents, while the remaining non-participating students were either unable to respond or absent due to illness during the data collection period. Most non-participants were individuals who generally would not be able to participate in any type of survey. This high response rate reinforces the validity of our social network mapping and ensures that our findings are representative of the student populations at these schools. Finally, through the survey, we obtained the permission to link the survey data with Norwegian registry data.

3.2 The Registry Data

Linking the survey data with the registry data provides us with detailed information on both the students and their parents, including educational backgrounds, income levels, employment details, and demographic characteristics.

The registry data includes information on each parent's highest achieved level of education, whether they are currently enrolled in any educational programs, and the specific type or field of education they have pursued. This information enables us to assess the educational environment within the students' households. Regarding employment and income, we have detailed data on the parents' job situations, including their workplace, occupation, industry sector, percentage of full-time equivalent (FTE) employment, and monthly salary in the periode from 2015 until 2020.

Additionally, we have comprehensive information on their income sources, such as yearly labor income, capital income, welfare transfers like unemployment benefits and child support, and total income. Financial obligations and assets are also documented, including taxes paid, real estate holdings, and property values for both primary and secondary residences. This allows us to comprehensively evaluate the socioeconomic status of each student's family.

The demographic details provided by the registry data include the parents' gender and year of birth, country of birth, immigration category, and date of immigration. Information on household composition indicates with whom the parents reside.

For the students, we have access to their academic records, including grades per subject—both final grades (*standpunkt*) and examination grades (*eksamen*). This data is crucial for assessing individual academic outcomes and the potential impact they may have on other students in their social networks. The registry data include detailed demographic information for each student, such as gender, birth month and year. The data also links students to their mother and father, allowing us to connect each student to their parents' data. We have records of the students' country of birth, immigration category, and date of immigration. Information on family structure includes the number of siblings and their birth order among their mother's children.

By integrating the registry data with our survey data, we can perform a detailed analysis of how various social factors—including family background, socioeconomic status, and household dynamics—interact within peer networks to influence network formation and academic performance.

3.2.1 Primary Outcome Variables

The primary outcome variables in our network effect analysis are the students' academic achievements, measured through their teacher-assigned grades (*standpunktkarakterer*) and their performance on national standardized tests. The teacher-assigned grades are final evaluations given by teachers in each subject at the end of each year in lower secondary school. They are intended to reflect the students' abilities at the end of the semester. These grades are also high stakes, as they directly contribute to the Grade Point Average (GPA) used for admission to high school.

In addition to teacher-assigned grades, we consider students' results from the national standardized tests administered in Grades 5 and 8. The tests are primarily graded automatically through digital systems, and mainly consist of multiple-choice questions and short answers that can be assessed by machines. Students take the tests on computers, and their answers are immediately sent to a central database for processing. These tests are created to objectively evaluate core competencies in arithmetic, reading, and English through blind assessments, providing an unbiased measure of student performance that complements the more subjective teacher evaluations. By incorporating both types of academic assessments, we aim to capture a comprehensive picture of student achievement. We also have access to each student's primary school and their performance on the national tests in arithmetic, reading, and English from the fifth grade. This information is utilized in our analysis as an instrument and to isolate the causal effect of friendships on subsequent academic performance.

Table 1: Summary Statistics

	Estimation sample							
	All		School 1		School 2		All (National)	
	mean	sd	mean	sd	mean	sd	mean	sd
Number of oneway friends	27.12	[19.26]	28.02	[17.29]	26.19	[21.09]	–	–
Number of twoway friends	10.37	[7.49]	11.56	[8.33]	9.15	[6.30]	–	–
Walking distance to school (km)	1.40	[0.83]	1.05	[0.56]	1.76	[0.91]	–	–
Female (%)	50.26	[50.04]	48.15	[50.05]	52.43	[50.03]	48.47	[49.98]
Born in Norway (%)	88.89	[31.45]	86.20	[34.55]	91.67	[27.69]	74.44	[43.62]
GPA	4.02	[0.84]	3.87	[0.85]	4.16	[0.81]	4.30	[0.81]
NT gpa 5th grade	51.65	[9.02]	51.13	[9.34]	52.18	[8.67]	48.36	[11.10]
NT gpa 8th grade	51.98	[9.08]	51.83	[9.09]	52.15	[9.09]	48.99	[9.82]
Number of parents	1.71	[0.48]	1.70	[0.46]	1.71	[0.49]	1.74	[0.63]
No parents (%)	1.03	[10.08]	0.34	[5.80]	1.74	[13.08]	9.91	[29.88]
1 parent (%)	27.18	[44.53]	28.96	[45.43]	25.35	[43.58]	6.34	[24.36]
2 parents (%)	71.79	[45.04]	70.71	[45.59]	72.92	[44.52]	83.76	[36.89]
At least 1 foreign parent (%)	32.82	[47.00]	37.04	[48.37]	28.47	[45.21]	32.96	[47.01]
Both parents foreign (%)	17.44	[37.97]	19.87	[39.97]	14.93	[35.70]	21.52	[41.10]
Avg. age of parent(s)	47.06	[5.04]	46.89	[5.42]	47.25	[4.60]	46.47	[5.56]
Avg. parent years of schooling	13.65	[3.38]	13.51	[3.58]	13.80	[3.16]	13.19	[2.56]
Parent high school or lower (%)	28.89	[45.36]	28.28	[45.11]	29.51	[45.69]	47.43	[49.93]
Parent $<$4 yrs higher edu (%)	38.12	[48.61]	36.36	[48.19]	39.93	[49.06]	41.85	[49.33]
Parent $\geq$4 yrs higher edu (%)	32.99	[47.06]	35.35	[47.89]	30.56	[46.14]	19.04	[39.26]
HH income ($1,000)	156.9	[109.9]	151.0	[101.4]	163.0	[117.9]	123.2	[212.4]
HH wealth ($1,000)	673.3	[519.2]	625.1	[462.1]	723.1	[568.8]	783.1	[7905]
HH wage income ($1,000)	139.4	[99.0]	136.0	[102.2]	143.0	[95.5]	106.1	[100.2]
Parent(s) on social security (%)	15.56	[36.27]	17.51	[38.07]	13.54	[34.28]	19.46	[39.59]
HH public transfers ($1,000)	10.4	[16.3]	11.5	[17.2]	9.3	[15.2]	11.1	[17.8]
Observations	585		297		288		239 931	

Notes: Means and standard deviations (in brackets) are shown for the 2019 sample of participating schools and for all Norwegian middle-school students (national).

Table 1 presents summary statistics for students from the two schools where we conducted the mapping of all friendships. The table provides an overview of key student characteristics, including the number of friendships (both one-way and reciprocal friendships) and the walking distance from students' residences to their schools. Beyond survey-based data, Table 1 also integrates registry data on gender, immigration background, academic performance, and various socioeconomic indicators. Parental characteristics are also included, covering total income, wage income, household wealth, social security receipt, and public transfers, as well as parental education levels and average age. All parental information is gathered through registry data which enables us to match students with their biological parents. The variables presented provide us with a comprehensive socioeconomic profile of the students in our sample and allow us to examine both the average differences between the two schools but also variation in characteristics across individual students.

To provide a broader context, Table 1 also presents summary statistics for all students in Norwegian middle schools from the same cohorts (2006–2008) we have surveyed. This comparison allows us to evaluate how representative our sample is relative to the national student population and to identify potential selection biases. Several notable patterns emerge from comparing the two tables. First, students in our sample are more likely to be born in Norway (88.9%) compared to the national average (74.4%). This suggests a lower representation of students with an immigrant background in the two schools where we conducted the friendship mapping. The academic performance, measured by GPA, is slightly higher in the national sample compared to our study sample. While the average GPA in our sample is 4.02, the national average is 4.30. However, the schools in our study perform better than the national average on standardized national tests, where all students take the same assessment. This discrepancy may reflect geographic differences in grading practices.

The socioeconomic background of the students also differs slightly from the national average. The parents of students in our sample have higher household income ($157k vs. $123k nationally) and higher wage income ($139k vs. $106k nationally). This may reflect the fact that our survey was conducted in a large Norwegian city, where income levels tend to be higher. However, household wealth in our sample is slightly lower than the national average ($673k vs. $783k). This may indicate regional differences in asset accumulation patterns, especially since the parents have a comparable average age (47.1 vs. 46.5 years). The proportion of students with at least one foreign-born parent is similar in our sample and the national average, both at approximately 33%. However, the share of students with two foreign-born parents is lower in the surveyed schools (17.4% vs. 21.5%), suggesting that our sample schools have a slightly different demographic composition than the broader Norwegian middle school population. These differences are important to keep in mind in the subsequent analysis of friendship formation and school environment dynamics.

4 Identification

4.1 Network formation models

To analyse student preferences in forming friendships, we will be using the model of Graham (2017). Let $A_{i,j} = 1$ denote that student i and j form a friendship. Then define

$$A_{i,j} = \mathbf{1}\{W_{i,j}\theta + V_i + V_j + U_{i,j} \geq 0\}$$

where $U_{i,j}$ is logistic. $W_{i,j}$ are link specific covariates, for example that person i and j are of the same gender. V_i is the relative popularity of individual i, and as such captures heterogeneity between students in the number of friendships.

To investigate spillover effects in student achievement, we estimate the following peer effect equation:

$$y_i = (Gy)_i\alpha + Z_i\gamma + X_i\beta + (GX)_i\alpha_2 + \epsilon_i. \tag{1}$$

Here, y_i represents the GPA of student i, while $(Gy)_i$ denotes the average GPA of student i's friends. The vector X_i is a set of individual student characteristics, and $(GX)_i$ represents the average characteristics of student i's friends. Z_i corresponds to student i's 5th-grade national exam score. To address endogeneity in $(Gy)_i$, we instrument it using $(GZ)_i$, which is the average 5th-grade national exam score of students i's friends.

We need an instrument due to the reflection problem discussed in Manski (1993), which induces correlation between $(Gy)_i$ and ϵ_i due to the peer effects in the network. As discussed in Bramoullé et al. (2009), identification of α necessitates restrictions both on the network structure and Z_i.

First, the instrument $(GZ)_i$ must be relevant, which requires $\gamma \neq 0$. Since the national test score is a measure of student ability, it is reasonable to believe it is a strong predictor of current GPA. In our results, we show that our first-stage regressions are generally strong across all our specifications.

Second, the network structure must exhibit sufficient non-transitivity in the links to ensure that $Z_i, (GZ)_i, and (G^2Z)_i$ are not co-linear. This ensures that the instrument provides independent variation, which is necessary for identification.

Finally, we need the instrument to be exogenous and excluded. Exogeneity means that $\mathbb{E}[\epsilon_i|(GZ)_i] = 0$, which we will discuss in the next section. For exclusion, the national test scores of a student's friend should not have a direct effect on the GPA except through the friends' GPA. To test this assumption, we can use the friends-of-friends national test score as an instrument and include the average national test scores of friends as a covariate. However, this approach makes our first stage very weak, and all the estimated coefficients are statistically insignificant in this specification, except for a student's own national test score.

4.2 Validity of the Instrument in the Peer Effect Model

In this section, we argue that our instrument—the average 5th grade national exam score of a students friends—is exogenous. We also consider possible counterarguments that could challenge its validity.

The national exam happened between three and five years before the students completed the survey and received their grades. This time gap reduces the likelihood that idiosyncratic shocks affecting student skills at the time of the national exam remain correlated with those influencing their current GPA. Any temporary fluctuations in ability or motivation during the exam are unlikely to persist over such a long period, thereby mitigating concerns about endogeneity.

A potential worry for the validity of 5th-grade national test scores as an instrument is the precence of correlated measurement error. Specifically, external factors during the test administration—such as noise in the exam room—could systematically affect students' scores. If students took the exam in the same room and were exposed to a noisy environment, their scores might be jointly impacted by these disturbances. In this case, the average national test score of friends would correlate with the measurement error of a student's own national test score, and therefore with ϵ_i. This would be a violation of the exclusion restriction.

Several factors reduce the likelihood of such correlated measurement errors. First, the national exam is conducted under standardized conditions designed to minimize external disruptions. Teachers are not allowed in the room during the exam, and schools implement measures to ensure a controlled testing environment. Second, the students in our sample went to many different primary schools. This means that even if there is something inducing measurement error in one school, it would not systematically correlate with the measurement error of students who attended other primary schools. This geographic dispersion further weakens concerns about school-specific biases affecting the instrument's validity.

5 Results

In this section, we present our main empirical findings. We begin by estimating our model of network formation within schools, leveraging detailed data to identify the characteristics that most strongly influence friendship choices and shape the broader social structure. Next, we introduce our estimates from the peer-effect model, which quantifies how these networks impact academic outcomes. Finally, we explore heterogeneity in peer effects within and across classes, as well as by gender and academic ability, to assess the extent to which certain subgroups are more influenced by their peers. Throughout the section, we also conduct robustness checks to evaluate the consistency of our findings across different model specifications. By integrating insights on both network formation and peer effects, this section provides a comprehensive perspective on peer dynamics and their role in shaping educational achievement.

Table 2: Logit Friendship

	Full sample	FE sample		Student controls		Parent controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Student characteristics:							
Same class	13.02***	13.56***	13.77***	13.58***	13.82***		
	(0.32)	(0.33)	(0.32)	(0.33)	(0.32)		
Same gender	15.81***	16.42***	16.34***	16.49***	16.33***		
	(0.43)	(0.44)	(0.38)	(0.44)	(0.38)		
Same elementary school	1.48***	1.59***	2.77***	1.92***	2.87***		
	(0.38)	(0.40)	(0.43)	(0.39)	(0.43)		
Same immigrant category	-0.06	-0.01	-0.74	1.53***	0.58		
	(0.51)	(0.53)	(0.97)	(0.48)	(0.93)		
Distance (km)	-0.81***	-0.81***	-0.56**	-0.76***	-0.56**		
	(0.21)	(0.21)	(0.25)	(0.20)	(0.25)		
NT gpa (diff)	-0.24	-0.23	-1.11***	-0.66***	-1.27***		
	(0.20)	(0.20)	(0.27)	(0.19)	(0.28)		
Parent characteristics:							
Same parent immigrant category	2.34***	2.28***	2.91***			2.49***	3.00***
	(0.45)	(0.47)	(0.59)			(0.47)	(0.65)
Avg. age of parents (diff)	-0.17***	-0.19***	-0.08			-0.20***	-0.11*
	(0.04)	(0.04)	(0.06)			(0.05)	(0.06)
Avg. parents years education (diff)	-0.34***	-0.33***	-0.11			-0.37***	-0.22**
	(0.07)	(0.07)	(0.09)			(0.08)	(0.10)
log HH income (diff)	0.02	0.00	-1.32***			0.05	-0.93*
	(0.31)	(0.33)	(0.45)			(0.37)	(0.50)
log HH wealth (diff)	-0.07	-0.08	-0.11			-0.18	-0.15
	(0.10)	(0.11)	(0.20)			(0.12)	(0.23)
Same parent social security status	2.23***	2.32***	2.59***			2.40***	3.30***
	(0.42)	(0.43)	(0.62)			(0.47)	(0.69)
Constant (de-meaned)	10.53***	10.97***	10.97***	10.97***	10.97***	10.97***	10.97***
	(0.17)	(0.17)	(0.15)	(0.17)	(0.15)	(0.19)	(0.19)
Individual fixed effects	No	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.179	0.181	0.359	0.173	0.355	0.010	0.156
Observations	28376	27233	27233	27233	27233	27233	27233

Note: This table presents average marginal effects from logit regressions where the dependent variable is whether both students have nominated each other as friends.

5.1 Network formation

In this section, we investigate the determinants of students' mutual friendship nominations. Table 2 presents the average marginal effects of each variable, with standard errors in parentheses. Columns (1) and (2) display results from the logit model without individual fixed effects, with Column (2) restricting the sample to students who name at least one friend. Column (3), our primary specification, adds individual fixed effects. In Columns (4) and (5), we incorporate only student characteristics, while Columns (6) and (7) focus on parental characteristics. In all specifications, we de-mean the dependent variables, so the constant term captures the overall likelihood that two students in the same grade form a mutual friendship—approximately 11 percent.

A key insight from Table 2 is that sharing the same class and being of the same gender emerge as the strongest predictors of mutual friendship. In Column (3), which includes individual fixed effects, students in the same class are roughly 14 percentage points more likely to nominate one another as friends. Likewise, students of the same gender have a 16 percentage-point higher likelihood of forming friendships compared to students of mixed gender. These effects are substantial and remain robust across all model specifications, including those with additional controls for individual fixed effects and parental characteristics.

Attending the same elementary school significantly increases the probability of mutual friendship, indicating that bonds formed in earlier educational stages often persist. However, we find no significant differences in friendship formation based on students' immigrant backgrounds, suggesting that shared national origin alone does not substantially influence friendship choices. By contrast, geographical proximity does matter: in our baseline model, living one kilometer farther apart reduces the likelihood of forming a friendship by 0.6 percentage points. Although statistically significant, the magnitude of this effect remains relatively modest.

Academic ability, measured by differences in fifth-grade national test scores, also exerts a small but significant influence on friendship formation. A one standard deviation gap in test scores lowers the probability of forming a friendship by 1.1 percentage points, indicating a slight tendency for students to seek out peers with similar academic performance.

Although weaker than student-level traits, parental background characteristics also shape friendship formation. Among these variables, shared immigrant background exerts the strongest influence: when one student has a foreign-born parent while the other does not, the average likelihood of a mutual nomination decreases by 2.9 percentage points. A similar decline emerges when parental income differences grow, as a one log-point gap in income lowers the chance of mutual nomination by 1.3 percentage points. By contrast, parental wealth does not appear to significantly affect the formation of friendships.

Social security status—defined as having at least one parent receiving disability benefits or social assistance—also plays a role in friendship formation. In our main model, students whose parents share the same social security status (or both lack it) are 2.6 percentage points more likely to nominate each other as friends. This suggests that similar socioeconomic conditions foster stronger social ties. In contrast, parents of similar age and education levels show no significant impact on

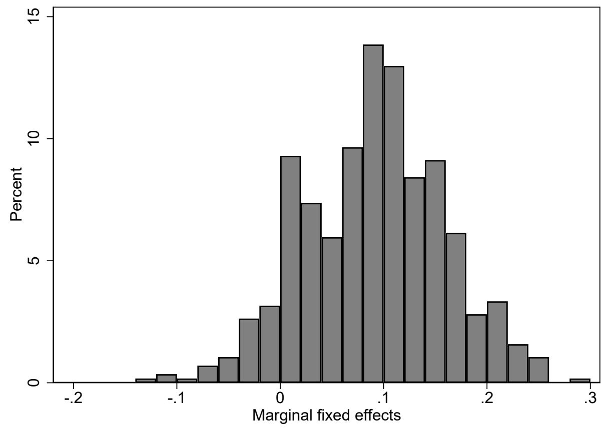

Figure 1: Student FE distribution from baseline model.

the formation of friendships.

The inclusion of fixed effects for each student in our network formation models significantly improves the model fit. Figure 1 shows the distribution of marginal fixed effects from our main model specification shown in Table 2, Column (3). We see that there is significant degree heterogeneity in our results, supporting our model choice

5.2 Network Formation: Interaction Within and Across Classes

We now extend our analysis to examine how student and parental characteristics influence friendship formation both within and across classrooms, as well as to explore the gender dimension. Table 3 reports results from these interaction models. Column (1) replicates the baseline fixed-effects specification from Table 2 for reference. Column (2) adds interactions between each independent variable and a dummy for being in the same class, while Column (3) lists the corresponding interaction terms. Columns (4) and (5) similarly introduce interactions based on whether students share the same gender.

The results in Table 3 indicate that same-gender friendships are more likely to form within the same class, compared to on average. Within classrooms, the probability of same-gender friendships is 4.8 percentage points higher than the average, which is implying that classroom social dynamics reinforce gender-based friendship patterns. By contrast, we find no evidence that the influence of other student characteristics shifts notably within the classroom. These findings suggest that the main drivers of friendship formation remain broadly consistent regardless of class composition.

Parental social security status seems to have a stronger influence on friendship formation across different classrooms than within the same classroom. This pattern, while not always significant, repeats for other parent characteristics as well. This suggests that while students from similar socioeconomic backgrounds are indeed more likely to become friends, this effect is driven by friendships outside the classroom. Inside the classroom, students are less related to the parental and socioeconomic backgrounds of their friends.

Table 3: Logit Friendship - Interaction models

	No interactions	Same class interactions		Same gender interactions	
	Baseline	Baseline	Interactions	Baseline	Interactions
	(1)	(2)	(3)	(4)	(5)
Student characteristics:					
Same class	13.77***	12.69***		12.30***	5.07***
	(0.32)	(0.40)		(0.38)	(0.76)
Same gender	16.34***	14.88***	4.83***	14.79***	
	(0.38)	(0.39)	(0.76)	(0.41)	
Same elementary school	2.77***	2.81***	-0.09	2.10***	2.51***
	(0.43)	(0.43)	(0.71)	(0.47)	(0.81)
Same immigrant category	-0.74	-0.59	-1.08	-0.97	0.88
	(0.97)	(1.05)	(1.00)	(1.05)	(1.16)
Distance (km)	-0.56**	-0.51**	-0.26	-0.38	-0.56*
	(0.25)	(0.25)	(0.27)	(0.26)	(0.29)
NT gpa (diff)	-1.11***	-1.24***	0.42	-1.21***	0.48
	(0.27)	(0.28)	(0.36)	(0.30)	(0.45)
Parent characteristics:					
Same parent immigrant category	2.91***	3.29***	-1.36	3.76***	-2.93***
	(0.59)	(0.61)	(0.84)	(0.67)	(1.06)
Avg. age of parents (diff)	-0.08	-0.08	-0.01	-0.08	-0.00
	(0.06)	(0.06)	(0.08)	(0.06)	(0.09)
Avg. parents years education (diff)	-0.11	-0.16*	0.27**	-0.05	-0.20
	(0.09)	(0.09)	(0.13)	(0.11)	(0.17)
log HH income (diff)	-1.32***	-1.51***	0.82	-1.22**	-0.42
	(0.45)	(0.45)	(0.61)	(0.49)	(0.71)
log HH wealth (diff)	-0.11	-0.18	0.20	-0.15	0.09
	(0.20)	(0.21)	(0.21)	(0.21)	(0.26)
Same parent social security status	2.59***	3.04***	-2.13***	2.16***	1.52*
	(0.62)	(0.64)	(0.82)	(0.66)	(0.91)
Constant (de-meaned)	10.97***	10.97***	10.97***	10.97***	10.97***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.359	0.364	0.364	0.363	0.363
Observations	27233	27233	27233	27233	27233

Note: This table presents marginal effects from a logit regression where the dependent variable is whether both students have nominated each other as friends.

5.3 Network Formation: Interaction Within and Across Gender

Our gender-interaction model further underscores how school structure influences friendship patterns. The results indicate that same-gender friendships are more likely to form among students who also attended the same elementary school. While parental immigrant background appears to matter for cross-gender friendships, it does not significantly affect same-gender friendships. In contrast, parental social security status emerges as a more influential determinant in generating friendships among students of the same gender.

Overall, the analysis underscores that shared environments and demographic similarities—particularly classroom assignment and gender—are the strongest predictors of student friendship formation. Although parental background and socioeconomic factors play a role, their effects are relatively modest compared to the pronounced influence of classroom structure and gender. This suggests that policymakers, through classroom assignment policies, have considerable power to shape friendship networks. By thoughtfully structuring classroom compositions, they can meaningfully influence social interactions and peer dynamics.

5.4 Peer effects

This section examines peer effects on students' academic performance. Table 8 presents the estimation results from our peer effect model outlined in Section 4. In the baseline specification (Column 1), the first-stage estimate suggests that a one-standard-deviation increase in the average national test scores of a student's friends raises the student's own GPA by 0.6 standard deviations. This first-stage result is highly significant, indicating the relevance of our instrument. Moreover, the effect remains remarkably stable across alternative model specifications, including those with or without student and parent covariates, as well as in the models with class fixed effects.

Turning to our 2SLS estimates, the baseline specification suggests that a one-standard-deviation increase in the average GPA of a student's friends raises the student's own GPA by about 0.54 standard deviations (SE 0.12). Including class fixed effects yields a slightly larger effect of 0.59 SD, and adding individual controls raises it further to 0.65 SD. In these specifications, we also include the average characteristics of each student's friends as control variables. When parental controls are added, the estimate remains substantial at 0.62 SD. In total, these findings indicate that peer effects are both persistent and large in magnitude, remaining robust across all our model specifications.

Table 4: Peer effects: Main estimates

Column:	(1)	(2)	(3)	(4)	(5)
Panel A: First stage					
Avg. friends NT: $(GZ)_i$	0.598***	0.594***	0.651***	0.436***	0.590***
	(0.065)	(0.053)	(0.048)	(0.065)	(0.052)
F-stat	84.3	124.0	180.9	45.2	129.5
Panel B: Second stage					
Avg. friends GPA: $(Gy)_i$	0.539***	0.587***	0.647***	0.549***	0.619***
	(0.123)	(0.119)	(0.110)	(0.201)	(0.138)
NT gpa	0.430***	0.427***	0.431***	0.348***	0.361***
	(0.051)	(0.050)	(0.051)	(0.049)	(0.047)
Student controls	No	No	Yes	No	Yes
Parent controls	No	No	No	Yes	Yes
Class fixed effects	No	Yes	Yes	Yes	Yes
Observations	580	580	580	580	580

Note:

To investigate potential heterogeneity in peer effects, Table 5 presents estimated peer effects across different subgroups based on individual characteristics. Panel A reports the first-stage results, showing the relationship between peer academic performance and the instrumented peer variable, while Panel B displays the second-stage 2SLS estimates of peer effects on students' GPA.

First, we compare peer effects by gender (Columns 1 and 2). The 2SLS point estimate is larger for males than for females (0.778 SD vs. 0.458 SD), suggesting stronger peer influences among male students. While point estimates suggest a potential gender difference, we lack the statistical precision to draw firm conclusions.

Next, we examine heterogeneity in peer effects based on students' academic ability (Columns 3 and 4), where we define high and low national test scores based on a median split of the sample. The estimated peer effects are 0.408 SD for high-performing students and 0.524 SD for low-performing students. Despite the slight difference in magnitude, the standard errors are large, and we find no statistically significant distinction in peer effects across these two groups.

In Columns 5–8, we further explore heterogeneity by examining the interaction between gender and academic ability, splitting the sample into high- and low-achieving males (Columns 5 and 6) and high- and low-achieving females (Columns 7 and 8). The results suggest that peer effects are particularly strong for low-achieving males (0.860 SD), while low-achieving females (0.367 SD), high-achieving males (0.388 SD) and high-achieving females (0.242 SD) exhibit much smaller peer effects. Only the estimated peer effect for low-achieving males is statistically significant, and the

Table 5: Peer effects: Heterogeneity

Column:	Male (1)	Female (2)	High NT (3)	Low NT (4)	Male H (5)	Male L (6)	Female H (7)	Female L (8)
Panel A: First stage								
Avg. friends NT: $(GZ)_i$	0.634***	0.513***	0.643***	0.578***	0.910***	0.592***	0.393***	0.613***
	(0.086)	(0.072)	(0.083)	(0.066)	(0.138)	(0.115)	(0.121)	(0.098)
F-stat	53.9	50.3	59.5	76.1	43.4	26.6	10.5	38.8
Panel B: Second stage								
Avg. friends GPA: $(Gy)_i$	0.778***	0.458**	0.408**	0.524**	0.388	0.860***	0.242	0.367
	(0.222)	(0.228)	(0.183)	(0.214)	(0.247)	(0.262)	(0.363)	(0.337)
NT gpa	0.328***	0.382***	0.914***	0.147**	0.909***	0.062	0.956***	0.212*
	(0.056)	(0.083)	(0.107)	(0.061)	(0.129)	(0.068)	(0.172)	(0.115)
Student controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	289	291	290	290	146	143	144	147

Note:

large standard errors are limiting our ability to draw definitive conclusions about differences in peer effects across these subgroups.

Overall, while our estimates suggest some variation in peer effects by gender and academic ability, the lack of statistical precision means we cannot confidently conclude that peer effects differ systematically.

6 Implications for class assignment

In this section we will investigate the effect of segregating classes by skill. Specifically, we will simulate from a counterfactual class assignment students are sorted into classes based on their national test scores. Our results indicate that this will lead to more friendships between highly skilled students, and less friendships between low and high skill students. We then investigate the effect these changes in the network linkage probabilities have on outcomes by simulating networks and outcomes based on our estimates.

More concretely, our new class structure generates a set of probabilities of student i and j linking, which we call $PA^{nc}_{i,j}$. From our model in Table 2 we also get baseline probabilities of linking, defined as $PA^{oc}_{i,j}$. We then generate two networks using the same draws $U_{i,j}$ as

$$A^{oc}_{i,j} = \mathbf{1}\{U_{i,j} \leq PA^{oc}_{i,j}\} \qquad A^{oc}_{i,j} = \mathbf{1}\{U_{i,j} \leq PA^{oc}_{i,j}\}$$

Figure 2 shows the difference between the number of friends of students between the original and new class structure from one of our simulation runs. As we see, the change in classes significantly affects the network structure.

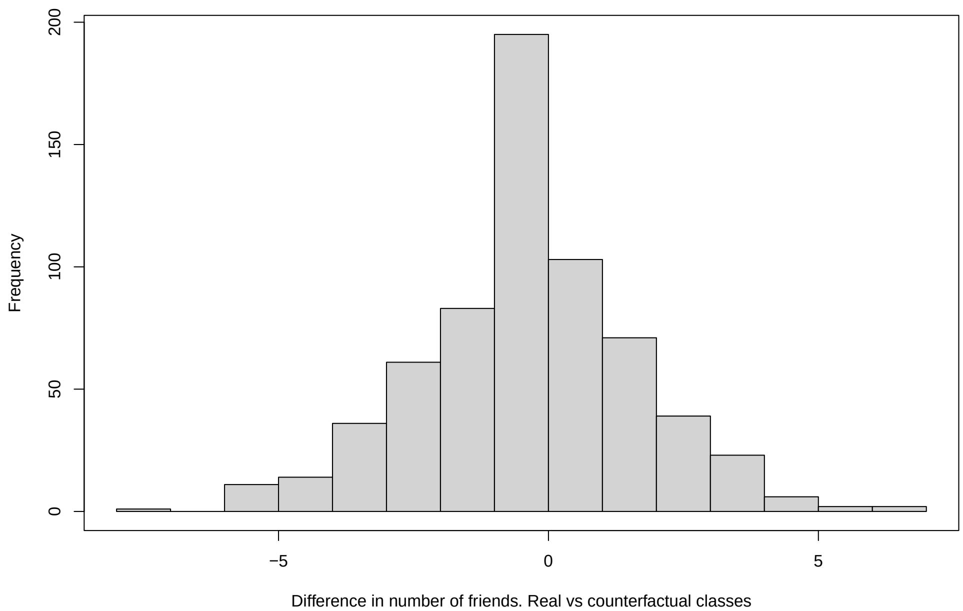

Figure 2: Distribution of differences in number of friends in an example simulated network

We repeat these simulations 30 000 times. This lets us see the possible effects the network can have on outcomes in the sample. We find that the network has a massive effect on the outcomes of the students, even if the peer effect is small. There exists networks that generate outcomes who's mean is below the lowest outcome in our sample. Similarly, there are networks that generate outcomes who's mean is above the highest outcome in our sample. For the majority of the networks, however, the effect on the average is within a standard deviation.

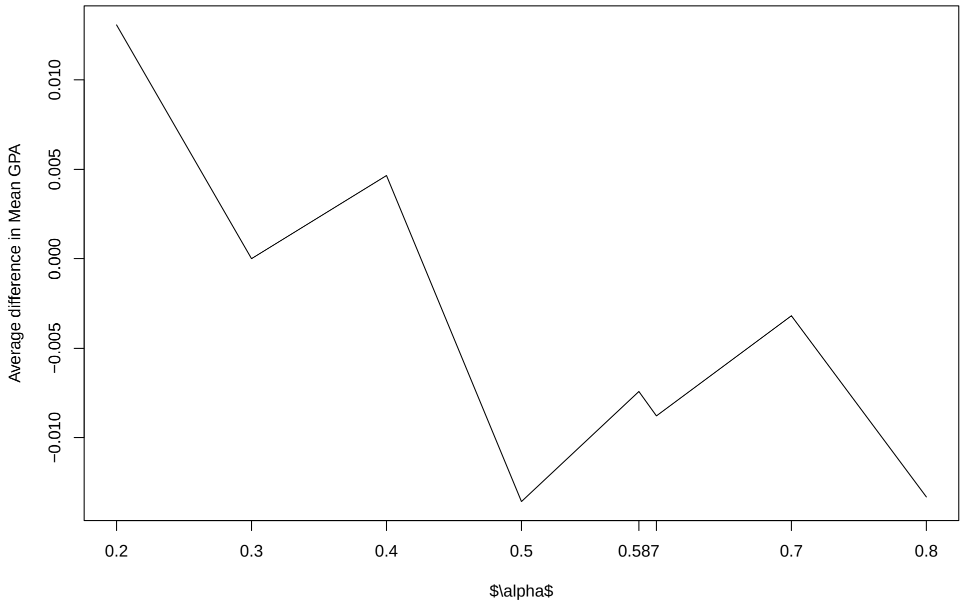

Figure 3: Effect on average outcome of changing class structure

We now know that the class assignments affect the networks, and that the network strongly affects outcomes. We now turn to investigating if the new classes generate "better" networks in terms of generating better average GPA scores for students. Figure 3 shows the average difference in average GPA between the two possible class structures. We show this for different levels of α, the coefficient on $(Gy)_i$ in Equation 1. We see that for smaller peer effects, the new classes lead to about a 1% standard deviation higher average GPA for students. However, as the peer effect becomes stronger, this effect falls to around -1%. These effects are fairly small and fairly noisy.

7 Conclusion

This paper examines the role of friendship networks in shaping academic outcomes by leveraging a unique dataset that combines a student survey with detailed registry data from two Norwegian middle schools. Our analysis provides new insights into the determinants of network formation, showing that friendships are primarily shaped by shared environments—most notably classroom assignment and gender—while parental background and broader socioeconomic factors play a more limited role. Furthermore, we estimate substantial peer effects on academic performance, finding that a one-standard-deviation increase in friends' GPA leads to an approximately 0.54 standard deviation increase in a student's own GPA. While peer effects appear stronger for male and high-achieving students, these subgroup differences are not statistically significant.

Beyond documenting the existence of peer effects, our study highlights the potential for classroom composition policies to influence student outcomes. Using our estimated network formation model, we simulate counterfactual classroom assignments and show that different friendship networks can lead to substantial variations in academic achievement. These results suggest that adjusting student placement within classrooms—while respecting students' natural preferences—could be a cost-effective policy tool for improving overall academic performance.

More broadly, our findings contribute to the growing literature on peer effects and network formation in education. They underscore the importance of considering social dynamics in educational policy design, particularly in settings where classroom structures can be adjusted to enhance learning environments.

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A Supplementary Results

Table 6: Logit Friendship: Extended model

	Full sample	FE sample		Student controls		Parent controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Student characteristics:							
Same class	13.02***	13.55***	13.77***	13.58***	13.82***		
	(0.32)	(0.33)	(0.32)	(0.33)	(0.32)		
Both male	17.13***	17.76***	25.06***	17.79***	24.43***		
	(0.46)	(0.48)	(5.09)	(0.48)	(5.10)		
Both female	14.34***	14.92***	7.62	15.03***	8.22		
	(0.47)	(0.48)	(5.09)	(0.48)	(5.10)		
Same elementary school	1.43***	1.54***	2.77***	1.86***	2.87***		
	(0.38)	(0.39)	(0.43)	(0.39)	(0.43)		
Both born in Norway	0.24	0.33	3.60	1.77***	-0.16		
	(0.52)	(0.54)	(7.90)	(0.48)	(4.65)		
Both not born in Norway	-1.14	-1.22	-5.08	-0.56	1.33		
	(1.83)	(1.86)	(8.10)	(1.75)	(4.98)		
Distance (km)	-0.79***	-0.79***	-0.56**	-0.77***	-0.56**		
	(0.20)	(0.21)	(0.25)	(0.19)	(0.25)		
NT gpa (diff)	-0.30	-0.31	-1.11***	-0.70***	-1.27***		
	(0.20)	(0.20)	(0.27)	(0.20)	(0.28)		
Parent characteristics:							
Both have parent(s) not born in Norway	3.22***	3.50***	8.74			3.22***	6.23
	(1.08)	(1.11)	(6.30)			(1.17)	(7.33)
Both have parent(s) only born in Norway	2.35***	2.23***	-2.92			2.45***	-0.22
	(0.46)	(0.48)	(6.22)			(0.48)	(7.27)
Avg. age of parents (diff)	-0.17***	-0.18***	-0.08			-0.20***	-0.11*
	(0.04)	(0.04)	(0.06)			(0.05)	(0.06)
Avg. parents years education (diff)	-0.33***	-0.33***	-0.11			-0.37***	-0.22**
	(0.07)	(0.07)	(0.09)			(0.08)	(0.10)
log HH income (diff)	0.18	0.19	-1.32***			0.09	-0.93*
	(0.32)	(0.33)	(0.45)			(0.37)	(0.50)
log HH wealth (diff)	-0.10	-0.13	-0.11			-0.22*	-0.15
	(0.11)	(0.11)	(0.20)			(0.12)	(0.23)
Both have parent(s) on social security	3.01***	3.40***	14.72***			4.24***	13.54**
	(1.12)	(1.16)	(5.14)			(1.24)	(6.21)
None have parent(s) on social security	2.29***	2.38***	-9.54*			2.32***	-6.94
	(0.42)	(0.44)	(5.06)			(0.48)	(6.13)
Constant (de-meaned)	10.53***	10.97***	10.97***	10.97***	10.97***	10.97***	10.97***
	(0.17)	(0.17)	(0.15)	(0.17)	(0.15)	(0.19)	(0.15)
Individual fixed effects	No	No	Yes	No	Yes	No	Yes
Pseudo R^2	0.182	0.184	0.359	0.176	0.355	0.010	0.156
Observations	28376	27233	27233	27233	27233	27233	27233

Note: This table presents marginal effects from a logit regression where the dependent variable is whether both students have nominated each other as friends.

Table 7: Logit Friendship: Heterogeneity

	School 1			School 2		
Grade:	8th	9th	10th	8th	9th	10th
Column:	(1)	(2)	(3)	(4)	(5)	(6)
Student characteristics:						
Same class	13.55***	13.21***	15.22***	14.15***	11.45***	13.81***
	(0.72)	(1.03)	(0.67)	(0.76)	(0.70)	(0.96)
Same gender	17.12***	21.08***	11.93***	17.47***	20.31***	10.81***
	(0.86)	(0.92)	(0.78)	(0.88)	(1.28)	(0.99)
Same elementary school	4.61***	2.11	3.48***	2.36*	-0.12	-0.03
	(0.88)	(1.31)	(0.88)	(1.35)	(0.94)	(1.12)
Same immigrant category	-3.07	-0.49	0.40	0.54	0.89	-1.77
	(1.90)	(3.54)	(1.60)	(2.53)	(2.52)	(3.10)
Distance (km)	-0.56	-3.47***	-1.55*	-1.36**	-1.33***	0.21
	(0.90)	(1.17)	(0.84)	(0.61)	(0.48)	(0.33)
NT gpa (diff)	-1.77***	-1.48	-0.45	0.02	-1.68**	-0.94
	(0.53)	(1.33)	(0.52)	(0.63)	(0.78)	(0.68)
Parent characteristics:						
Same parent immigrant category	4.75***	5.72***	3.40***	-1.17	-0.39	3.47**
	(1.24)	(1.87)	(1.02)	(1.90)	(1.99)	(1.46)
Avg. age of parents (diff)	-0.37***	0.20	-0.09	-0.15	0.05	-0.03
	(0.12)	(0.18)	(0.10)	(0.14)	(0.13)	(0.16)
Avg. parents years education (diff)	0.06	-0.46	-0.49**	0.07	-0.04	0.10
	(0.20)	(0.34)	(0.19)	(0.24)	(0.19)	(0.27)
log HH income (diff)	-1.44	-2.33	-1.33	-2.24**	-0.28	1.13
	(1.01)	(1.47)	(0.89)	(0.96)	(1.24)	(1.43)
log HH wealth (diff)	0.14	0.66	-0.15	-0.15	-0.56	-0.33
	(0.57)	(0.64)	(0.34)	(0.55)	(0.43)	(0.51)
Same parent social security status	2.42**	4.32**	1.85	-3.17	3.95***	1.95
	(1.10)	(1.97)	(1.20)	(2.96)	(1.27)	(1.36)
Constant	11.09***	18.41***	8.29***	12.02***	8.39***	8.51***
	(0.35)	(0.47)	(0.33)	(0.37)	(0.34)	(0.43)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.354	0.409	0.365	0.346	0.356	0.320
Observations	5564	3655	4851	5149	4849	3160

Note: This table presents marginal effects from a logit regression where the dependent variable is whether both students have nominated each other as friends.

Table 8: Peer effects: Main estimates including control variables

Column:	(1)	(2)	(3)	(4)	(5)
Panel A: First stage					
$(GZ)_i$	0.598***	0.594***	0.651***	0.436***	0.590***
	(0.0651)	(0.0533)	(0.0484)	(0.0649)	(0.0519)
F-stat	84.3	124.0	180.9	45.2	129.5
Panel B: Second stage					
$(Gy)_i$	0.539***	0.587***	0.647***	0.549***	0.619***
	(0.1230)	(0.1192)	(0.1096)	(0.2010)	(0.1382)
NT gpa	0.430***	0.427***	0.431***	0.348***	0.361***
	(0.0513)	(0.0496)	(0.0511)	(0.0485)	(0.0474)
Female			0.600***		0.612***
			(0.1239)		(0.1156)
Female (avg. of friends)			-0.347**		-0.380**
			(0.1672)		(0.1787)
Born in Norway			-0.087		-0.158
			(0.1381)		(0.1538)
Born in Norway (avg. of friends)			-0.274		-0.295
			(0.3185)		(0.3585)
Both parents foreign				0.120	0.092
				(0.0957)	(0.1084)
Both parents foreign (avg. of friends)				-0.170	-0.113
				(0.2324)	(0.2456)
Avg. age of parent(s)				0.013**	0.015**
				(0.0060)	(0.0058)
Avg. age of parent(s) (avg. of friends)				-0.016	-0.018
				(0.0170)	(0.0165)
Avg. parent years of schooling				0.047***	0.043***
				(0.0136)	(0.0131)
Avg. parent years of schooling (avg. of friends)				-0.010	-0.013
				(0.0368)	(0.0314)
log HH income				0.212***	0.225***
				(0.0541)	(0.0533)
log HH income (avg. of friends)				0.209	0.214
				(0.1851)	(0.1762)
log HH wealth				-0.015	-0.016
				(0.0208)	(0.0203)
log HH wealth (avg. of friends)				-0.030	-0.019
				(0.0520)	(0.0461)
Parent on social security				-0.024	-0.018
				(0.0940)	(0.0896)
Parent on social security (avg. of friends)				0.122	0.215
				(0.2332)	(0.2364)
Class fixed effects	No	Yes	Yes	Yes	Yes
Observations	580	580	580	580	580

Note: