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The Toll of Turnover: Network Instability, Well-Being, and Academic Effort in 56 Middle Schools

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Abstract: This article examines whether network instability—namely, the extent of turnover in a person's social network over time—is a distinct social process that affects individual well-being. Using a unique two-wave network data set collected in a field experiment that involved more than 21,100 students across 56 middle schools, we find a strong negative association between network instability and well-being and academic effort at the individual level, independent of other types of network change effects. We assess whether the negative effect of network instability remains when the source of instability is exogenous, the result of participation in the randomized intervention. Network instability leads to negative consequences even in this context, negatively impacting students who directly participated in the intervention. For nonintervention students in treatment schools, the intervention stabilized their social networks. We discuss the implications of these findings for studies of social networks and collective action.

Keywords: social networks; network instability; well-being; academic effort; schools; field experiments

The set of relationships any individual has changes throughout the life course as people age, move, join and leave organizations like schools and workplaces, and otherwise exert their preferences for some people more than others. Despite a long sociological tradition concerned with the impact of social instability on societies, neighborhoods, families, and individuals (Amato 2000; Amato and Sobolewski 2001; Durkheim [1893] 2014; Kornhauser 1959; Polanyi [1944] 2001; Sampson 1988; Sampson and Groves 1989; Sampson et al. 1997), the literature on social networks has devoted relatively little attention to instability in social networks as a distinct process with distinct effects on outcomes (see Borgatti and Halgin 2012). Instead, most existing research on network change documents the extent of instability in networks without exploring its impact or it examines the effects of changes in the composition of people's networks rather than the effects of the network instability itself. In this article, we examine the role that network instability has on life outcomes, disentangling network instability—which is defined formally with the Jaccard index as the overlap between the set of ties one has at one period and the ties one has at another (see Wellman et al. 1997)—from the other network processes and outcomes with which such change is often associated. What might appear as a purely methodological puzzle has important theoretical and policy implications. As but one example, if network stability is as or more important for well-being than the number of social ties one has, interventions aimed at increasing

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social support may, through the addition of social ties and the resultant instability of such additions, actually make people worse off.

The article makes use of a unique data set collected in the context of a school antibullying field experiment, which assessed the social networks of more than 21,100 students in 56 middle schools over the course of a school year. Scholars have demonstrated the importance of peer networks for explaining a wide variety of outcomes among adolescents, from health behaviors like smoking (Mercken et al. 2010; Schaefer, Haas, and Bishop 2012) to adolescents' risk of contracting sexually transmitted diseases (Bearman, Moody, and Stovel 2004) to patterns of peer conflict (Faris and Felmlee 2011; Paluck, Shepherd, and Aronow 2016). Yet here, like in much of the social network literature, the emphasis has been on explaining the effects of the structure of adolescent networks rather than on explaining the effects of instability within these networks.

After reviewing the literature on network change and instability, our analysis proceeds in three parts. We begin by examining, observationally, the relationship between endogenous individual-level network instability—namely, changes to relationships that occur naturally over the course of the school year, outside of the experimental context—and individual-level outcomes. We focus on two types of individual-level outcomes that have implications for students' personal and academic success: school-related well-being (assessed by an index of school belonging, depressive symptoms, and involvement in conflict with other students) and academic effort, which is assessed through a measure of homework effort. This examination follows in the tradition of work linking social relationships to quality of life. We isolate the relationship between network instability and well-being by accounting for other explanations that might impact well-being.

Nevertheless, the relationship we establish between network instability and outcomes might still be driven by processes of selection—specifically, there may be unobserved variables that drive both network instability and negative individual-level outcomes. Thus, we next turn to an experimental context in which people's networks were made unstable exogenously: an antibullying intervention in which a small (20 to 32 person) group of students within each treatment school was randomly selected to participate in a school-level intervention group that was responsible for developing and implementing an antibullying program within their school. The intervention was not designed explicitly to alter students' social networks; rather, the change in social networks for treatment students was a byproduct of the design of the antibullying program. We show that assignment to this intervention destabilized students' networks and that this destabilization had similar negative consequences as those of endogenous network instability.

We conclude by exploring the relationship between the experimental intervention and outcomes at the school level. Because we know from previous research that the antibullying intervention had a net positive impact on treatment schools (Paluck et al. 2016), the question is whether the intervention worked despite destabilizing students' networks or whether it worked in part through the stabilization of students' social networks overall, despite its destabilizing impact on the students most directly involved. We find support for the latter explanation—that, although the intervention destabilized the networks of those most directly involved in it compared with their counterparts in control schools, it stabilized the networks of students in treatment schools overall.

Across these analyses, we find evidence that social instability is associated with negative outcomes, independent of other mechanisms, which suggests that social instability is indeed a distinct and distinctly negative social process among adolescents. We conclude with a discussion of the implications of these findings for scholars of social networks and scholars of processes of social change.

Network Instability as a Distinct Social Process

A long sociological tradition has been concerned with the ways in which social instability erodes the norms and practices through which lives are given meaning (Durkheim [1893] 2014; Kornhauser 1959; Polanyi [1944] 2001). In *Suicide*, for instance, Durkheim ([1893] 2014) argued that periods of rapid social transformation could lead to increases in the suicide rate because such change destabilized existing norms and led to feelings of aimlessness and anomie. Polanyi ([1944] 2001:39–40) likewise suggested that rapid changes in social structure were often more detrimental to the well-being of societies than the direction of such changes. Although these theorists were concerned with macrostructural change rather than changes to people's local networks, their work seems to imply that rapid changes within local networks might be similarly detrimental to individuals' well-being. At a mesolevel, "stability" remains a salient metaphor through which sociologists understand the health of neighborhoods and communities (Sampson 1988; Sampson and Groves 1989; Sampson et al. 1997) and the health of families (Amato 2000; Amato and Sobolewski 2001). These lines of macrolevel theory and mesolevel scholarship seem to have one relatively clear implication for scholars of social networks: that instability in one's network over time ought to have negative consequences, independent of factors such as the structure of one's network or characteristics of those ties that are gained or lost. Previous research has not tested this proposition.

Network scholars have learned a good deal about the characteristics and life contexts of individuals who keep or lose social ties over time, the characteristics of the alters with whom they keep or lose those ties, and the nature of the relationships that are kept or lost (e.g., Fischer and Offer 2020; Marin and Hampton 2019; Martin and Yeung 2006; Small, Pamphile, and McMahan 2015). Some research examines the individual differences associated with network instability (e.g., Sasovova et al. 2010).

Another wide body of literature has shown that the loss of familial or other strong ties has a range of negative effects on psychological and physical well-being (Amato and Sobolewski 2001; Berkman et al. 2000; Mueller 1980; Paykel 1978). Yet within this existing literature, it is impossible to distinguish between the effect of network instability on the one hand and the effect of the number of strong ties one has on the other. In these studies, usually of network loss, one might reasonably conclude either that negative outcomes are caused by network instability or that they are caused by the lower number of strong ties that an individual has in the latter period. Some of the most rigorous research to date has suggested it is not instability in ties so much as the lower absolute number of supportive ties that explain such negative results. For instance, in a study of youth in foster care, Perry (2006) found that the negative psychological effects of network disruption (i.e., the loss of prior ties) were almost entirely attenuated by their replacement with similarly supportive ties, which implies that instability in and of itself may be unimportant.

If it is the number of ties one has that matters for well-being rather than the instability one experiences in one's network, then any association between instability and well-being should disappear once accounting for the number of ties one has in each period. Such a result would be consistent with a traditional social capital perspective, which treats ties as resources: a larger number of ties would be associated with more resources, information, and support, whereas a smaller number of ties would be associated with the opposite (Coleman 1988; Granovetter 1973; Portes 1998; Putnam 2000). On the other hand, if instability in one's network is associated with negative outcomes even after controlling for the size of one's network at each period, this would be evidence that instability may have a more direct effect on outcomes than traditional social capital models predict.

The association between instability and individual-level outcomes might also be explained by the qualities of peers to whom ties are gained or lost as a result of network change, or differences in the structure of the individual-level networks that are associated with network change. Against a tide of research demonstrating the importance of social capital as a source of support, information, and opportunity for mobility, the notion that some types of social ties may, in some contexts, be liabilities, is a subtle but persistent undercurrent (Coleman 1988:S105; Domínguez and Watkins 2003; Fischer 2005; Valente et al. 2007). New ties, by definition, are those with whom one has not had time to build relations of trust and so may be more likely than persistent ties to be parasites, bad influences, or sources of bad information (Burt 2000). If new network ties are less likely to be as positive than old network ties, then it could be that gaining new ties (or losing old ties) degrades the average quality of one's social network and is thus negatively associated with well-being. Such a result would be consistent with a social influence model of social networks (Friedkin [1998] 2006), which posits that the loss of a negative influence would have a positive effect on well-being, whereas a gain of a negative influence would have a negative effect. Here, again, the association between network instability and negative outcomes would be spurious, and any association between network instability and outcomes should disappear once accounting for the quality of ties one has in each period.

Likewise, instability in one's network might be associated with changes in the structure of one's ego network. The addition of new ties, or loss of old ties, may introduce imbalance into one's network and lead to negative outcomes through the tension that such imbalance introduces; conversely, it could be that new ties tend to be relationships with people who increase network balance, increasing the transitivity of people's ego networks in ways that positively reinforce social support (Heider 1946). From this perspective, one might expect network change within a large group to have an impact on individuals whose own personal networks remain unchanged, as the ties people have are related to the social structures within which they are embedded (Haynie 2002; Uehara 1990). And yet, here again, the association between network instability and well-being outcomes would be spurious, driven by differences in the structure of one's network rather than by network instability itself.

In sum, in order to establish network instability as a distinct social process, with independent effects on social life and well-being, one must measure the effects of instability, accounting for the number and characteristics of one's ties and for the structure of the individual's and group's network at the two points in time between which network change occurs. Previous literature has not yet made such distinctions, and this is a gap our analysis is able to fill.

Effects of Types of Network Instability

Even if one is able to establish network instability as a distinct social process, it may still be that different types of instability have different implications for individuals' well-being. First, network instability as measured by the Jaccard index conflates two analytically distinct processes: the severance of ties and the addition of ties. Even net of the effect of the number of ties on outcomes, it may be that the process of forming new ties has a different effect than the process of severing old ones. Given loss aversion (Tversky and Kahneman 1991), for instance, one might expect a loss of positive ties to have a stronger negative effect than the positive effects of positive tie additions. In this case, the absolute number of one's ties from one period to another might remain the same, but one might feel less well off, as the negative effect of one's loss was greater than the positive impact of one's gain.

The effects of network instability may also depend on the social processes by which it comes about. Network instability brought about by the decisions of individuals within a network—endogenous instability—may have different effects than instability incidentally introduced by an intervention that changes the context of interaction across a network. There is some evidence to suggest that endogenous network instability might have more positive effects than random, exogenously induced instability. In a cooperation experiment, Rand, Arbesman, and Christakis (2011) found that participants were able to enforce positive norms more easily when they were at liberty to make and break ties as they wished, as compared with when they were unable to change their networks or had these networks randomly changed.

On the other hand, we might expect that the effects of an exogenous intervention like the antibullying intervention studied here, which is explicitly intended to support positive norms around relationships, might be more positive than endogenous processes, which may or may not support positive norms. A substantial literature on social movements observes how social networks serve as channels for recruitment and influence in collective action, and how movement campaigns reciprocally transform people's networks (Gould 1995; Kim and Bearman 1997; McAdam and Paulsen 1993). It would be consistent with this body of evidence if the kinds of network instability that occurred alongside or as a result of concerted campaigns for social improvement had different effects than the network instability that was a result of individual decision making or exogenous shocks not linked to social change attempts. One pathway by which this may occur is through providing different narratives or justifications for individuals to draw on in understanding instability in their social networks.

The above review, and the outstanding questions it identifies, serves as a roadmap for the analyses that follow. We begin by exploring the relationship between endogenous network instability and individual-level outcomes. We then leverage the experimental context to more precisely identify the nature of the relationship between network instability and individual-level outcomes within the context of a prosocial intervention that seems, on its face, unlikely to lead to negative individual-level outcomes. Finally, we discuss the relationship between network instability and outcomes at the school level in order to understand whether the antibullying intervention improved school outcomes despite inducing network instability in treated schools or whether it did so through the stabilization of the networks of treated schools.

Data and Methods

We assess the effect of network instability on individual- and school-level outcomes using a unique longitudinal network study of a year-long field experiment in 56 middle schools, 28 of which conducted a student-led campaign against peer harassment. Paluck et al. (2016) has evaluated the effects of the intervention on patterns of peer conflict and harassment in the schools and within-school network-based influence effects. Overall, the intervention succeeded in reducing administrative reports of conflict by 25 percent in treated schools compared with control schools.

In this article, we focus on the relationship between social instability and outcomes among students in both control and treatment schools (21,124 students completed both waves of the survey and are included in the current study). We are thus able to examine the implications of individual-level social network change that arises from different sources—network change that was the result of endogenous decision making by individuals in control schools compared with network change driven in part by the exogenous shock of the intervention program in treatment schools.

At each school, all students in the middle grades (5th to 8th grades were eligible) were surveyed at the same time and day twice during the year: 3 or 4 weeks after the beginning of the school year in the fall, prior to randomization to condition, and in last 3 weeks of the academic year in the spring, after the 10 intervention program meetings, which we describe in more detail below, had concluded.

Student Surveys

The survey included a network nomination section, a personal background and activities section, and an attitudes and experiences section. The mean survey nonparticipation rate, a product of parents opting out of their student participating and of student absence, was 5.6 percent of the school population (23,415 students completed the first survey). Schools were randomized to treatment condition after the first survey; rates of nonparticipation are unrelated to treatment status.

Table 1: Descriptive statistics for network stability and change measures ($N = 21,124$).

	Mean	SD	Range	Percentage of Students with Minimum Value (%)	Percentage of Students with Maximum Value (%)
Relationship Stability					
Wave 1 to Wave 2	0.30	0.18	0–1	4.61	0.28
Proportion Gained Ties	0.36	0.16	0–1	4.27	0.58
Proportion Lost Ties	0.33	0.16	0–1	2.96	0.58
Number of Ties, Wave 1	7.96	2.48	0–10	0.01	0.47
Number of Ties, Wave 2	8.26	2.34	0–10	0.01	0.52

Note: Relationship stability wave 1 (W1) to W2 is defined as the proportion of retained ties, also known as the Jaccard index.

Network nominations. For the network nominations portion of the survey, all participating students received a roster of the entire school, which was arranged into sections by grade and gender and was alphabetized by first name, where each student was assigned a three-digit number. Students were asked to provide the three-digit numbers of their peers for network nomination questions. The measure of social ties used in the analyses in this article asked students to report who they had "decided to spend time with (in school, out of school, or online)" from their school in the last few weeks. Nominations were capped at 10. The phrasing was designed to elicit a behavioral, student-directed measure of social connections. Six and a half percent of students left this section blank.

Our key explanatory variable, network stability, is derived from students' answers to this "spend time" question on the wave 1 and wave 2 surveys. We calculate stability as the overlap between a student's nominees at wave 1 and their nominees at wave 2 (also referred to as the Jaccard index, which was calculated as the number of retained ties divided by the sum of retained, dropped, and added ties). We also calculate the proportion of peers nominated at wave 1 who were not nominated at wave 2 (the number of dropped ties divided by the sum of retained, dropped, and new ties) and the proportion of peers who were not nominated at wave 1 but who were nominated at wave 2 (the number of new ties divided by the sum of retained, dropped, and new ties).

As shown in Table 1, the mean Jaccard index value for all students who reported data at both waves is 0.30 (SD = 0.18), meaning that, on average, seventy percent of a student's "spend-time" network consisted of peers who were either dropped or added between wave 1 and wave 2. This Jaccard index is similar to that reported in other studies of adolescents, for example, 0.24 in the AddHealth data (Schaefer et al. 2009), and 0.28 and 0.31 among secondary students in Glasgow schools (Veenstra and Steglich 2012). On average, as a proportion of the total ties that students had across either wave, students gained more ties than they lost (mean 0.36, SD 0.16 for gained ties; mean 0.33, SD 0.16 for lost ties). The average number of reported ties at wave 1 was slightly less than 8; at wave 2, the average was 8.26. Full descriptive statistics are available in Table A of the online supplement.

School-related well-being. A series of survey questions also asked students to report on their feeling of belonging at school, depressive symptoms, and their experience of conflict with other students in both survey waves. Responses to the measures, reverse-coded when appropriate, were summed in a school-related well-being index. These measures were selected as measures of student well-being in middle school that were (1) substantively important and (2) not direct measures of the presence or absence of peer relationships and thus not conceptually overlapping with the network instability measure. The nature of interactions with peers, reflected in two of the measures below, is an important aspect of students' well-being during adolescence (Martin and Huebner 2007). The results we report below are robust to using other measures of school-related student well-being and to examining each of the measures independently instead of as an index.

Students reported their sense of belonging at the school using a binary measure: "I feel like I belong at this school." Eighty-one percent of students reported feelings of belonging at wave 1, and 71 percent did so at wave 2. About 18 percent of students who reported feeling that they belonged at wave 1 reported that they did not feel that way at wave 2.

Depression was assessed using a binary question adapted by work on depression from the Patient Health Questionnaire-2 (Kroenke, Spitzer, and Williams 2003), which indicates that rumination on emotion is a central feature of depression: "During the past month, I have often been bothered by feeling sad and down." Fifteen percent of students reported depressive symptoms at wave 1, whereas 24 percent did so during wave 2. About 14 percent of students who did not report depression during wave 1 did so at wave 2. This measure was reverse-coded for the index.

To gauge students' evaluations of their own participation in conflict at their school, students were asked a binary question about whether they agreed with the statement, "I have a lot of conflict with other students at this school." Eighteen percent of students reported having a lot of conflict during wave 1, whereas 23 percent did so during wave 2. About 15 percent of students who did not report peer conflict during wave 1 did so during wave 2. This measure was accompanied by a behavioral assessment of whether students had "stayed home from school because of problems with other students," which is frequently used as an indication of severe problems with peers in the bullying literature (Vail 1999). Five percent of students reported having stayed home during wave 1, whereas 8 percent did so during wave 2. About 6 percent of students who did not report staying home during wave 1 did so during wave 2.

Academic effort. During both waves of the survey, students reported on their academic effort by answering a binary question about whether they agreed that they "do a lot of homework." Forty-three percent of students reported doing a lot of homework during wave 1, whereas 39 percent did so during wave 2. About 18 percent of students who reported doing a lot of homework during wave 1 did not report doing so during wave 2; about 13 percent of students who did not report doing a lot of homework during wave 1 did report doing so during wave 2.

Alternative Explanations and Controls

Behavior of new peers. To account for changes in the behavior of one's network peers that may correspond to network instability, we calculate the proportion of one's new peers (those with whom the respondent did not report a relationship during wave 1 but did during wave 2) who, during wave 1, themselves reported involvement in conflict, dating (a risk factor for conflict; see Felmlee and Faris [2016]), beliefs conducive to conflict ("you have to be mean to survive" at the school), and, for the analysis of academic effort, doing a lot of homework. We chose these measures of peer behavior and attitudes because of their empirical relationship with school-related well-being and academic effort and because they are traits, that, if one's peers had, would bear on one's own outcomes due to peer influence.

Network structure metrics. We use each school's complete "spend time" network to calculate students' betweenness centrality using the *igraph* package in R. This measure first determines the shortest path between each pair of actors in the network and then calculates the percentage of those paths that include the focal actor. The more frequently a student is included in the shortest, or more direct, path between two other students, the higher their betweenness centrality score. We use betweenness centrality because it is a structural measure of exclusive social status in middle schools (Callejas and Shepherd 2020; Faris and Felmlee 2011) that is likely associated with well-being in that social status and well-being in adolescence are closely related (Sweeting and Hunt 2014).

We also used the complete spend time network to calculate the proportion of each student's network neighbors that are connected to each other out of the total possible number of connections, a statistic known as the local clustering coefficient. We might expect that declines in the proportion of neighbors who are connected to each other introduce more imbalance in network relationships, which is associated with worse outcomes (e.g., Helliwell and Wang 2011). These measures help us distinguish the impact of network instability from the impact of associated changes in students' positions within the broader student network.

Personal characteristics and attitudes. Students also provided information about a number of personal characteristics, including their racial identity and grade in school, and a number of binary measures, including gender, whether they predominantly spoke English at home, whether their mother went to college, whether someone in their family recently lost a job, whether they have moved houses in the last few years, whether they date students at their school, whether they plan to go to college, whether they use Facebook, whether they believe that "sometimes you have to be mean to others as a way to survive at this school" (a measure of attitudes about the nature of peer interaction at the school), and whether "Friends say I have a really nice house" as an age-adjusted measure of relative socioeconomic status.

In many of the models, we include controls for respondent indegree (number of nominations he/she received from peers as someone they spend time with) and for change in the number of outgoing nominations from wave 1 to wave 2 to ensure that the Jaccard index effects are not an artifact of change in the number of network nominations over time.

Overview of the Intervention

The intervention program was designed to test the effect of the behaviors of salient students on school-wide perceptions of peer harassment norms and behaviors. To do so, the field experiment used two levels of randomization, both between schools and within schools. Between schools, half of the schools ($n = 28$) were randomly selected to receive an anti-peer harassment, bullying, and conflict program consisting of 10 meetings throughout the school year. Schools were assigned to blocks of four, and randomized to receive the treatment or not within these blocks.[1] The purpose of block randomization is to maximize the possibility of a balanced distribution of types of schools in both control and treatment groups.

In each of the 28 of 56 schools randomly assigned to receive the intervention, Paluck et al. (2016) selected a group of students representing 15 percent of the school population—blocked by gender, grade, and clustering coefficient—to be eligible for the intervention (*eligible students*). Researchers randomly assigned 50 percent of that group to be invited to participate in the anticonflict intervention as *intervention students*. The size of the intervention group ranged from 20 to 32 students, scaled by the size of the school, and represented between 4 and 15 percent of the school population. This produced a total of 728 treatment students across the 28 intervention schools.[2] At control schools, the students who would have been intervention students had the school been randomized to receive the intervention program were interviewed by researchers once during the school year for between 15 and 45 minutes about student life at the school.

Four trained research assistants conducted the intervention program, which helped intervention students identify common conflict behaviors at their school, so that the intervention could address the conflicts specific to each school. Intervention students were encouraged to become the public face of opposition to these types of conflicts. The program consisted of 10 meetings of activities and discussions with the selected students from November to May of the school year, within each of the 28 intervention schools. The 9th of the 10 meetings at each treatment school was the culminating event of the intervention. The intervention model was similar to a grassroots campaign in which the intervention students took the lead. Notably, it lacked an educational or persuasive unit regarding adult-defined problems at their school. To maintain a standardized intervention, the research assistants followed the same semistructured scripts and activity guides.

Four principles guided the creation of the intervention meeting curriculum, designed by the researchers and research assistants, for the 10 meetings of the intervention program. First, intervention students were responsible for identifying the issues of concern with respect to peer harassment, bullying, and conflict at the school and for addressing them. This motivation stemmed from the recognition of the often profound differences in the types of peer conflict problems experienced at different schools. Second, activities provided opportunities for intervention students to generate strategies to address the specific conflicts they identified and to reward other students for prosocial behaviors. Third, program activities provided students with specific actions they could take in response to behaviors of others in the school. Fourth, the program sought to make the initiatives of the treatment students public and visible to others at the school. Treatment students practiced describing the purpose of the group, and what it sought to achieve at the school, to others.

Though the intervention was not designed explicitly to change students' networks, two features of the intervention program led to the expectation that the intervention would change patterns of interaction over time, though the two features predict change in different ways.[3] First, the intervention brought together a randomly selected group of mixed gender and grade students (treatment students) and asked them to interact with each other through activities and discussions every 2 weeks throughout the school year. The intervention allowed students who did not have regular contact with each other to get to know each other, in effect creating the conditions to rewire the social network. Previous research illustrates the importance of opportunities for high-quality interaction and collaboration toward a common goal for creating friendships (Blau 1977; Festinger 1950), conditions that the intervention program provided.

Because the intervention students came from different social groups, to the extent that they made new friendships through participation, they would have created new ties and generated greater social instability. Given findings regarding the likelihood of individuals becoming friends with their friends' friends, treatment students who became friends in the intervention program may have increased the number of new social relations among their friends as well (Cartwright and Harary 1956; Davis 1970). Thus, we might expect greater social instability over time as a result of new ties among intervention students and their friends.

Another key feature of the intervention relevant to changes in social networks is the content of the program, which focused on how to help students create strong friendships and positive peer interactions. Specifically, program activities encouraged treatment students to help their friends feel accepted and valued and to spread this ethos to other students at the school beyond friends. The program also encouraged the participating treatment students to see themselves as experts about their schools and as changemakers at their schools. Based on the program content, we might expect the intervention to encourage either network stability (as treatment students work to strengthen both their own and others' existing friendships) or instability through growth, as intervention students reach out beyond their existing networks to encourage positive relationships among students more generally.

Table 2 provides descriptive information about network stability (the Jaccard index), and network change (proportion of gained ties, proportion of lost ties), along with network structure at wave 2 (clustering coefficient and betweenness centrality), for different types of students. Using *t* tests, we compare these metrics between (1) students who participated in the intervention program, (2) other students within treatment schools (including eligible students who were not assigned to the intervention program, students with network ties to treatment students, students with no network exposure to treatment students, and an aggregation of all students other than intervention students), and (3) counterfactual intervention students in control schools.

These summary statistics by student type ought to be interpreted with caution for three related reasons. First, exogenous changes from the intervention program for intervention students have ramifications throughout the networks of treatment

Table 2: Descriptive statistics for network stability and change measures by type of student.

	Intervention Students in Treatment Schools	Control Students in Treatment Schools	Network Peers of Intervention Students in Treatment Schools	No Network Exposure to Treatment Students in Treatment Schools	All Nonintervention Students in Treatment Schools	Counterfactual Intervention Students in Control Schools
Proportion Retained Ties Wave 1 to Wave Jaccard Index 2,	0.31 (0.18)	0.30 (0.19)	0.31 (0.17)	0.29* (0.18)	0.29 (0.18)	0.32 (0.18)
Proportion Gained Ties Wave 1 to Wave 2	0.38 (0.17)	0.38 (0.18)	0.34† (0.14)	0.38 (0.17)	0.37† (0.16)	0.36* (0.17)
Proportion Lost Ties Wave 1 to Wave 2	0.31 (0.16)	0.31 (0.17)	0.35† (0.15)	0.33† (0.16)	0.34† (0.16)	0.31 (0.15)
Clustering Coefficient, Wave 2	0.15 (0.08)	0.16 (0.08)	0.16 (0.08)	0.15 (0.08)	0.15 (0.08)	0.16 (0.08)
Betweenness Centrality, Wave 2	0.008 (0.008)	0.007 (0.007)	0.008 (0.009)	0.006† (0.007)	0.007† (0.007)	0.008 (0.010)
n	673	665	7,419	6,063	9,631	673

Notes: Standard deviations are listed in parentheses. $^{*}p < 0.05$, $^{\dagger}p < 0.01$ for t test comparisons with intervention students in treatment schools (first column).

schools, leading to spillover effects and thus complicating the interpretation of comparisons across groups within treatment schools. Second, as explained above, intervention-eligible students were not randomly selected from treatment schools as a whole but rather were selected based on blocking by gender, grade, and clustering coefficient, which further complicates comparisons of different groups within schools. Treatment-eligible students and non-eligible students thus differ from each other in important ways that are likely related to their experienced network stability.[4] Finally, summary statistics by type of student mask substantial school-level variation in network stability.

Because of spillover effects within treatment schools and preexisting differences between intervention-eligible and non-eligible students within treatment schools, our examination of the network effects of the intervention does not compare the networks of intervention students with nonintervention students within schools. Instead, we compare the networks of different groups of students within treatment schools with their counterparts in control schools, which allows for a more precise comparison.

Analytic Strategy

We conduct three main analyses in this article to establish the nature of the relationship between network instability and well-being and to examine whether the source of that network instability mitigates the negative impact on well-being. First, we examine the relationship between endogenous network instability and school-related well-being outcomes and school engagement. Second, we examine whether the effect of network instability on well-being and achievement depends on the process by which this instability is brought about. Finally, we examine—at the school level—the causal impact of the anti-peer harassment intervention on network instability.

In our first set of analyses, we fit ordered logistic regressions for the school-related well-being index and logistic regression for academic effort, regressing the outcome measures on the amount of network stability (measured by the Jaccard index), net of controls. We then add a series of variables, including the number and quality of network ties and position within and the structure of the larger network, in order to examine whether the effect of network instability on well-being and achievement can be accounted for by these other factors that are common in the social networks and well-being literature. We report these analyses using multiple imputation for missing nonnetwork control variables, but the results are the same when using list-wise deletion.

In our second analysis, to test the effect of school-level treatment on network instability at the individual level, we fit a linear model regressing the Jaccard index on school treatment condition, including school-level fixed effects, among treatment students and students who were selected prior to school randomization to participate in the intervention but whose school was randomized to the control condition (counterfactual treatment students) ($n = 1,472$). We follow this analysis with a test of whether the effect of network instability on well-being varies by the process by which that instability was brought about (endogenous to the network or exogenous to the network, as in the case of the experimental intervention). To do so, we use an ordered logistic model to compare the well-being and school effort outcomes of intervention students in treatment schools to those of counterfactual treatment students in control schools. Following Mize (2019), we include terms for the Jaccard index and for school-level condition as well as for the interaction between the two. We use random assignment of the school (school treatment) to assess whether the effect of social instability on well-being varies based on whether those students were in schools randomly assigned to treatment, and thus the students participated in the intervention program in which they experienced an exogenous shock to their network, or in control schools, in which their instability was an endogenous feature of network change over the course of the year. Of course, some instability among the networks of intervention students is endogenous, but the intervention program also introduced exogenous change that students in control schools did not experience. These analyses include controls (individual characteristics and network characteristics) and school-level fixed effects. We report the results of these effects using multiple imputation for the nonnetwork control variables.

Finally, to test the experimental effect of school-level treatment on network instability among all students in treatment and control schools, we fit a linear model regressing Jaccard index on school treatment condition, including school-level fixed effects. We first do this for all students in the sample ($n = 21,124$) and then adapt this model to compare particular subsets of students based on their ties to treated students. This allows us to test whether the effects of the intervention on network instability depend on one's proximity to the intervention. We also report the results of these effects using multiple imputation for the nonnetwork control variables; the results are the same using list-wise deletion.

A concern with using regression models with network data is that the assumption of the independence of observations is violated, as observations in a network are, by definition, interrelated. The concern with violating the assumption of independence of observations is that standard errors will be biased downward. In order to address this concern, all results are reported using clustered robust standard errors in which the clusters in each school network are calculated based on different clustering algorithms (either edge-betweenness or walktrap methods, calculated using the igraph package in R). The logic of this approach is based on the assumption, demonstrated in a large body of empirical work, that the characteristics and behavior of individuals, including status and perceived conflict, are likely to be more similar between people who spend time together and thus report ties to each other. Clusters represent groups of students, within a particular school, with more dense ties to each other than to out-group students, and we would assume that characteristics and behaviors within groups are more similar than across them. By clustering standard errors by those network clusters, we account for the interdependencies between observations. The substantive results are the same regardless of the clustering algorithm (and regardless of whether errors are clustered in this way or not); we report standard errors clustered by the edge-betweenness method.

Results

Effects of Network Stability on Well-Being and Academic Effort

We first turn to an analysis of the relationship between endogenous network instability and well-being, assessed by an index of school-related well-being (range from 0 to 4, higher values indicate better well-being), and academic effort, assessed by student reports of doing a lot of homework (a binary variable). We examine separate models for each outcome variable. In each model, the dependent variable is the wave 2 value of the outcome, controlling for the wave 1 value. We also control for several individual-level characteristics and activities (either time invariant, or measured at wave 1) that we know, based on previous research and on descriptive analyses in these data, are substantively related to social integration and effort in school: demographic characteristics (gender, grade, race, language spoken at home), activities and aspirations (dating, doing homework, college aspirations), social life (attitude about peer conduct, friends at the school, being on Facebook), wave 1 network indegree (a measure of being socially accepted), and family characteristics (whether a parent recently lost a job, an age-adjusted measure of relative wealth, whether mother went to college, whether they moved recently). We also control for being a treatment student to account for differences based on participation in the intervention, and change in the reported number of outdegree nominations from wave 1 to wave 2, to account for changes in the baseline number of nominations that might account for the effect of network instability. Results are shown in Table 3.

Basic models. The relationship between network stability and the wave 2 index of school-related well-being, controlling for wave 1 well-being and individual characteristics, is significant and positive: net of other factors, having more network stability is associated with a 2.46 odds ratio of a higher well-being index score at wave 2.

Table 3: Logistic regression of well-being and academic effort on network stability (reported as odds ratios).

	Well-Being Index, Wave 2	Academic Effort, Wave 2
Tie Stability	2.46†	1.71†
	(0.08)	(0.09)
Demographic Characteristics		
Male	1.72†	0.75†
	(0.03)	(0.04)
Grade	0.96	1.05*
	(0.02)	(0.02)
White	0.95	0.99
	(0.04)	(0.05)
Language Other Than English at Home	0.97	1.15†
	(0.03)	(0.04)
Activities and Aspirations		
Date, Wave 1	0.79†	0.84†
	(0.04)	(0.04)
Do Lots of Homework, Wave 1	0.99	4.05†
	(0.03)	(0.03)
Intend to Go to College, Wave 1	1.24†	1.51†
	(0.04)	(0.05)
Social Life		
Believe "you have to be mean to survive," Wave 1	0.74†	0.86†
	(0.04)	(0.04)
Most Friends Go to the School, Wave 1	1.10	1.07
	(0.04)	(0.05)
On Facebook, Wave 1	0.80†	0.81†
	(0.03)	(0.03)
Indegree, Wave 1	1.01†	0.99
	(0.004)	(0.004)
Family Characteristics		
Parent Lost Job, Wave 1	0.84†	1.01
	(0.04)	(0.04)
House Is Nice (Wealth), Wave 1	1.13†	1.12*
	(0.03)	(0.03)
Mother Went to College	1.03	1.09*
	(0.04)	(0.05)
Recently Moved, Wave 1	0.84†	0.99
	(0.04)	(0.04)
Other Contols		
Change in Outdegree Nominations, Wave 1 to Wave 2	1.02†	1.02†
	(0.006)	(0.006)
Treatment Student	1.06	1.12
	(0.08)	(0.09)
Wave 1 Measure	2.32†	...
	(0.02)	...
Negative Log-Likelihood	–22,717	–12,210
n	20,030	20,821

Notes: Models include school fixed effects. Standard errors are clustered by network cluster and appear beneath odds ratios. Results shown use multiple imputation for missing values for nonnetwork control variables; the findings for Jaccard index are robust to analyses using list-wise deletion of missing values. $*p < 0.05$, $\dagger p < 0.01$.

Table 4: Logistic regression of well-being and academic effort on gained and lost ties (odds ratios).

	Well-Being Index, Wave 2			Academic Effort, Wave 2		
	1	2	3	1	2	3
Proportion Lost Ties	0.22† (0.15)	...	0.24† (0.19)	0.46† (0.16)	...	0.71 (0.21)
Proportion Gained Ties	...	0.25† (0.15)	0.49† (0.20)	...	0.39† (0.17)	0.49† (0.21)
Negative Log-Likelihood	–22,724	–22,733	–22,717	–12,215	–12,211	–12,210
n	20,030	20,030	20,030	20,821	20,821	20,821

Notes: Models include individual-level controls and school fixed effects. Standard errors are clustered by network cluster and appear beneath odds ratios in parentheses. Control variables are: wave 1 measure; demographic characteristics and behaviors (race, language spoken at home, age-adjusted socioeconomic status, gender, grade, date at wave (W1), homework at W1, whether most friends go to the school, college aspirations, mother's education, whether someone in family lost a job recently, whether moved recently, belief that you have to "be mean to survive," and Facebook usage); intervention student status (dummy variable), indegree in W1, change in number of outdegree nominations, W1 to W2. Results shown use multiple imputation for missing values for nonnetwork control variables; the findings for Jaccard index are robust to analyses using list-wise deletion of missing values. $*p < 0.05$, $\dagger p < 0.01$.

Likewise, having greater network stability, controlling for individual characteristics and activities, is associated with a 1.71 odds ratio of academic effort at the end of the school year, controlling for academic effort at the beginning of the year.[5]

Including the network stability measure significantly improves model fit for both of these outcomes, as assessed using a likelihood ratio test (change in log-likelihood when including Jaccard is –57, $p < 0.0001$ for well-being and –14 for academic effort, $p < 0.0001$).

Gained versus lost ties. We next assess whether these results were sensitive to the type of network change that students experienced (gaining more ties compared with losing ties). In a typical social capital model, gaining more ties should have positive effects on well-being compared with losing ties. In models considering the proportion of lost ties (see Table 4, model 1), the proportion of gained ties (model 2), and the proportion of lost and gained ties together (model 3), both gained and lost ties are associated with reporting less positive well-being and less academic effort at wave 2. These findings indicate a negative effect of network instability, regardless of whether that instability is driven by the loss or gain of ties.

We next turn to an analysis of whether the effect of network stability on these outcomes can be attributed to other factors, specifically a change in the nature of the peers one is connected to or a change in network structure accompanying relational change.

Accounting for behavior of network neighbors. One mechanism by which network instability might relate to declines in well-being is if students who have more network instability also experience changes in the nature of the behavior of their peers, given the abundant evidence of the role of peers in adolescents' outcomes. This may happen if students systematically lose ties to network neighbors with positive behaviors (e.g., students who do not participate in conflict or who do a lot of homework) and/or gain ties to network neighbors who participate in negative behaviors (e.g., students who participate in conflict or who do not do a lot of homework). Consequently, we examine the effect of network instability on well-being and academic effort, controlling for changes in the behavioral composition of one's peers. Specifically, we expect that having more new peers who are involved in conflict, have beliefs that support conflict, and date other students, would lead to declines in well-being. Similarly, having fewer new peers involved in conflict and more new peers who do a lot of homework should contribute to academic effort.

The correlations between network stability and change in peer behavior are low, indicating that network instability and change in the behavior of one's peers are conceptually unrelated ($r = -0.05$ for the proportion of new peers who report dating at wave 1, $r = -0.03$ for the proportion of new peers who report participating in conflict at wave 1, $r = -0.04$ for the proportion of new peers who report that "you have to be mean to survive" at school at wave 1, $r = 0.07$ for the proportion of new peers who report doing a lot of homework at wave 1).

Results for the models with controls are in Table 5. For both outcomes, the same relationship between network stability and well-being or academic effort reported above remains even when controlling for change in the behavioral composition of one's peers. Thus, we find that the negative effect of network instability on well-being is not accounted for by changes in the behavioral composition of one's peers.[6]

Network structure change. Another possible mechanism by which network instability might be related to worse well-being is by affecting structural features of one's network that are associated with well-being. As we noted above, we examine whether the effect of network instability on well-being is mediated by changes in one's betweenness centrality—a measure of exclusive social status in middle schools (Callejas and Shepherd 2020; Faris and Felmlee 2011)—or by changes in local network closure (the proportion of neighbors who are connected to each other, the clustering coefficient). Declines in betweenness centrality may be associated with worse well-being to the extent that the effects of changes in social status are likely associated with worse treatment from peers, which could reduce well-being (e.g., Gould 2002). Similarly, declines in the proportion of neighbors who are connected to each other introduce more imbalance in network relationships, which is associated with worse outcomes (e.g., Helliwell and Wang 2011).

In order to test whether the effects of network instability can be accounted for by changes in network structure relevant to well-being, we analyze the relationship between network stability and our key outcomes, controlling for these structural network changes. The correlation between the Jaccard index and change in network structure for both measures is very low ($r = 0.002$ for change in betweenness centrality; $r = -0.01$ for change in the clustering coefficient), indicating that network instability does not co-occur with changes in network structural position. Whether we control for changes in betweenness and clustering coefficient separately or together, the same relationship between network stability and well-being reported above remains. Results are presented in Table 6. The negative effect of network instability on well-being and academic effort is not mediated by changes in network structure associated with worse well-being and effort outcomes.[7]

Table 5: Logistic regression of well-being and academic effort on network stability controlling for behavior of new network peers (odds ratios).

	Well-Being Index, Wave 2		Academic Effort, Wave 2	
	1 Without Test Variables	2 With Test Variables	3 Without Test Variables	4 With Test Variables
Tie Stability (Jaccard Index)	2.83† (0.09)	2.83† (0.09)	1.95† (0.10)	1.88† (0.10)
Behavior of Network Neighbors				
Proportion of New Neighbors Who:				
Date	...	1.06 (0.06)	...	0.76† (0.07)
Have Conflict	...	0.79† (0.06)	...	0.83* (0.08)
Believe "you have to be mean to survive"	...	0.93 (0.06)	...	0.78† (0.08)
Do Lots of Homework	...	...	...	1.52† (0.06)
Negative Log-Likelihood	–21,870	–21,862	–11,776	–11,725
n	19,331	19,331	20,053	20,053

Notes: Models include individual-level controls and school fixed effects. Standard errors are clustered by network cluster and appear beneath odds ratios. We report results including all three test variables, but results are robust to including only one or subsets of these three variables, or including other measures of new peer behavior. Control variables are: wave 1 (W1) measure; demographic characteristics and behaviors (race, language spoken at home, age-adjusted socioeconomic status, gender, grade, date at W1, homework at W1, whether most friends go to the school, college aspirations, mother's education, whether someone in family lost a job recently, whether moved recently, belief that you have to "be mean to survive," and Facebook usage); intervention student status (dummy variable), indegree in W1, change in number of outdegree nominations, W1 to W2. Results shown use multiple imputation for missing values for nonnetwork control variables; the findings for Jaccard index are robust to analyses using list-wise deletion of missing values. $*p < 0.05$, $\dagger p < 0.01$.

The Effects of Exogenous Network Change

Our first set of analyses supports the idea that instability in an individual's network is associated with negative individual-level outcomes, independent of other network effects. But because these analyses are based on observational data, it is impossible to disprove the idea that this association may be spurious, driven by unobserved variables that predict both network instability and negative individual outcomes.

In our next set of analyses, we turn to the experimental context—the school-level intervention in which a select group of students in treatment schools were chosen, at random, to participate in groups charged with developing and implementing programs to improve school climate. Our intuition is that, because the intervention involved bringing these students together into new groups, these students will have had their networks rendered unstable as a result of participation, as compared with their counterparts in control schools. But we also view this as a somewhat conservative test for the idea that network instability leads to negative outcomes,

Table 6: Logistic regression of well-being and academic effort on network stability controlling for changes in network structural position (odds ratios).

	Well-Being Index, Wave 2		Academic Effort, Wave 2	
	1 Without Test Variables	2 With Test Variables	3 Without Test Variables	4 With Test Variables
Tie Stability (Jaccard Index)	2.46† (0.08)	2.48† (0.09)	1.71† (0.09)	1.71† (0.09)
Changes in Network Structure				
Change in Clustering Coefficient	. . .	0.87 (0.18)	. . .	0.99 (0.21)
Change in Betweenness Centrality	. . .	0.37 (2.00)	. . .	0.85 (2.29)
Negative Log-Likelihood	–22,619	–22,619	–12,160	–12,160
n	19,950	19,950	20,730	20,730

Notes: Models include individual-level controls and school fixed effects. Standard errors are clustered by network cluster and appear beneath odds ratios. We report results including both network structure change variables, but results are robust to including only one of these variables or to including alternative measures of network structure. Control variables are: wave 1 measure; demographic characteristics and behaviors (race, language spoken at home, age-adjusted socioeconomic status, gender, grade, date at wave 1, homework at wave 1, whether most friends go to the school, college aspirations, mother's education, whether someone in family lost a job recently, whether moved recently, belief that you have to "be mean to survive" and Facebook usage); and intervention student status (dummy variable), indegree in wave 1, change in number of outdegree nominations, wave 1 to wave 2. Results shown use multiple imputation for missing values for nonnetwork control variables; the findings for Jaccard index are robust to analyses using list-wise deletion of missing values. $*p < 0.05$, $\dagger p < 0.01$.

as the intervention was designed explicitly to lead to positive changes in school climate. In this context, is certainly seems plausible that network instability caused by participation in the intervention would be associated with positive changes.

We first use an individual level, ordinary least squares regression framework to test whether participation in the intervention groups made participants' networks more unstable. Table 7 reports the results of regressions comparing the stability of intervention group participants against their counterparts in control schools (counterfactual treatment students, i.e., those who would have been in the intervention groups had their school been assigned to the treatment condition). Students who themselves participated in the intervention (intervention students) in treatment schools experienced an average decline in their network stability of 12 percent; the coefficient is –0.10 when also controlling for individual-level characteristics related to network instability in order to account for any differences in the composition of the population of intervention and counterfactual treatment students. Thus, we find evidence that students in treatment schools assigned to the intervention experience more instability than the group to which we are comparing them, which suggests that involvement in the intervention does indeed render student networks more unstable.

Having established that participation in the intervention groups leads to more network instability, we compare the effect of network instability on well-being and

Table 7: Ordinary least squares regression of network stability on school treatment status for intervention students and counterfactual treatment students in control schools.

	Between Schools (Intervention Students)	
	1 No Controls	2 Controls
Treatment School	-0.12^{*} (0.05)	-0.10^{*} (0.05)
Intercept	$0.37^{\dagger}$ (0.03)	$0.25^{\dagger}$ (0.04)
Adjusted R^2	0.07	0.11
n	1,346	1,346

Notes: Models include individual-level controls and school fixed effects. Standard errors appear beneath nonstandardized coefficients and are clustered by network cluster. Controls are individual-level characteristics associated with network instability to ensure that the results are not due to an imbalance of characteristics among intervention and counterfactual treatment students: race, language spoken at home, age-adjusted socioeconomic status, gender, grade, date at wave 1, homework at wave 1, whether most friends go to the school, college aspirations, mother's education, whether someone in the family lost a job recently, whether they moved recently, and Facebook usage. Results shown use multiply-imputed values for missing control variables in order to minimize the effect of observations lost when using list-wise deletion. $*p < 0.05$, $\dagger p < 0.01$.

academic effort among these students with the effect of network instability among similar students in control schools (counterfactual treatment students). Again, the goal of this analysis is to assess whether the type of instability experienced by those directly involved in the intervention—namely, those whose instability was brought about at least in part as a result of the exogenous shock of the antipeer harassment program—has the same negative consequences as the instability we previously observed across students as a whole. Figure 1 displays the predicted values for well-being and academic effort as a function of network stability (Jaccard index) by school treatment status for intervention students and counterfactual treatment students in control schools (these models include an interaction term for school treatment and Jaccard index [Mize 2019]; coefficients are reported in Table B of the online supplement). Based on this evidence, net of controls or excluding controls, we find that network instability generated exogenously by involvement in the antipeer harassment program does not protect against the negative effect of network instability.

Prosocial Intervention and Network Stability at the School Level

The antibullying intervention for which this data set was collected did, indeed, have positive effects among treatment schools (Paluck et al. 2016). This leads to something of a puzzle in light of the previous section, where we show that those students most directly involved in the intervention had their social networks destabilized by such involvement and that this destabilization was associated with the same negative effects on their well-being as the endogenous network instability examined in the first analysis. Two possible explanations for these

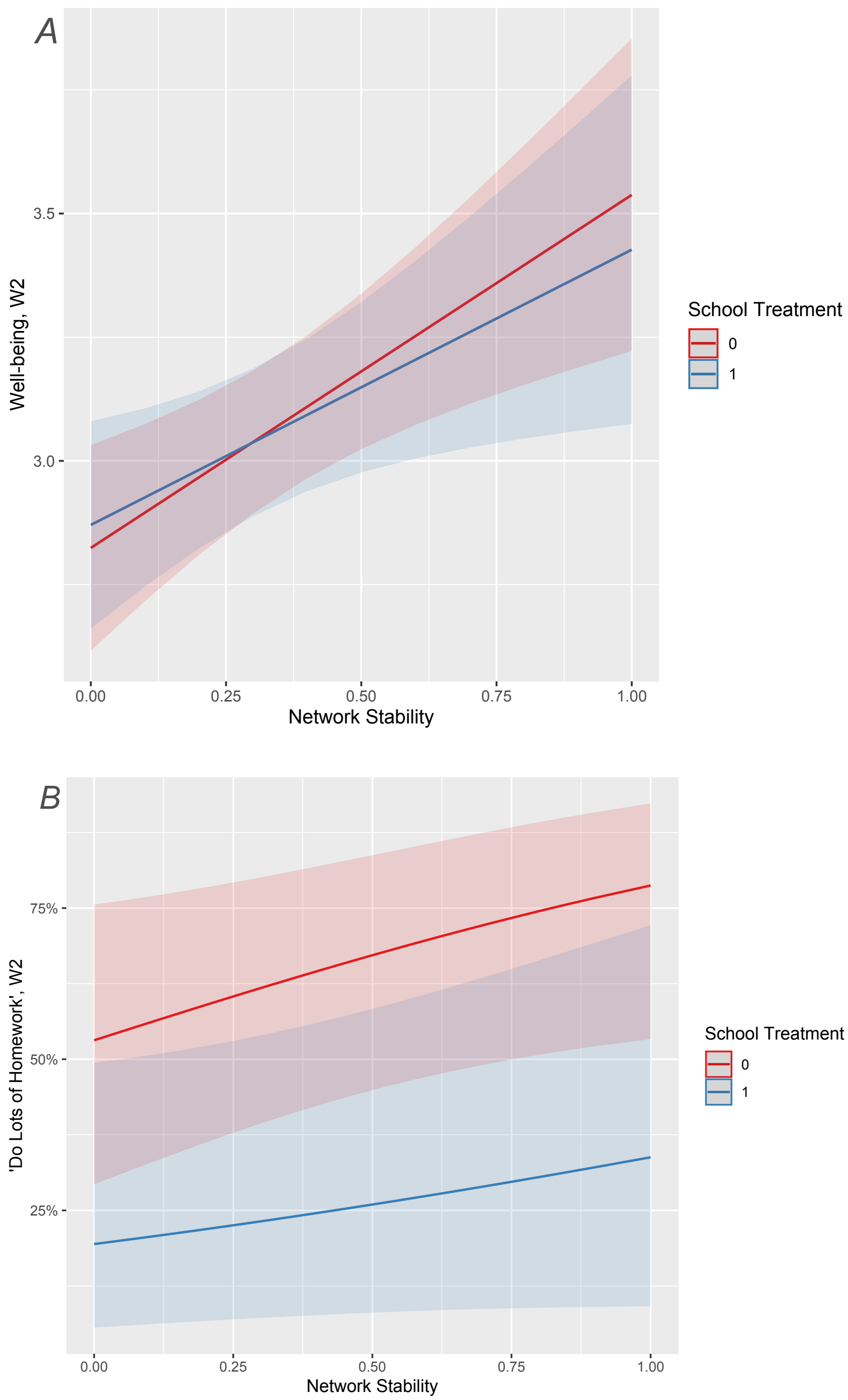

Figure 1: Plot of predicted values of effect of network stability (Jaccard index) on (*A*) well-being and (*B*) academic effort by school treatment status (0 = control; 1 = treatment) for intervention students and counterfactual treatment students in control schools ($n = 1,472$).

Table 8: Ordinary least squares regression of network stability on school treatment status, by treatment status of student.

	1 All Students	2 Intervention Peers, Wave 1	3 Students With No Exposure to Intervention, Wave 1
Treatment School	$0.05^{\dagger}$ (0.02)	$0.10^{\dagger}$ (0.03)	0.04^{*} (0.02)
Intercept	$0.02^{\dagger}$ (0.01)	$0.14^{\dagger}$ (0.03)	$0.17^{\dagger}$ (0.01)
Adjusted R^2	0.10	0.12	0.10
n	21,124	7,419	12,359

Notes: Models include individual-level controls and school fixed effects. Standard errors appear beneath nonstandardized coefficients and are clustered by network cluster. Controls are individual-level characteristics associated with network instability to ensure that the results are not due to an imbalance of characteristics among intervention and counterfactual treatment students: race, language spoken at home, age-adjusted socioeconomic status, gender, grade, date at wave 1, homework at wave 1, whether most friends go to the school, college aspirations, mother's education, whether someone in the family lost a job recently, whether they moved recently, and Facebook usage. Results shown use multiply-imputed values for missing control variables in order to minimize the effect of observations lost when using list-wise deletion. $*p < 0.05$, $\dagger p < 0.01$.

seemingly contradictory findings exist. The first is that the intervention succeeded in spite of destabilizing networks in treatment schools—specifically, that there were countervailing effects of the intervention that made up for the negative impact of instability on outcomes. The second is that although the intervention destabilized the networks of students most directly involved in it, compared with counterfactual students in control schools, it worked in part by stabilizing the networks of students in treatment schools as a whole, relative to their control school counterparts.

Table 8 extends the analyses conducted in Table 6 beyond intervention students, comparing the network stability of all students in treatment schools (first together, then separated by their relationship to the intervention) with their counterparts in control schools. Comparing all students in treatment schools with all students in control schools, we find that being in a treatment school is associated with a 5 percent average increase in one's Jaccard index (when controlling for other characteristics), indicating that students in treatment schools experience more network stability than do students in control schools. This is somewhat surprising, given that the treatment destabilized networks of those students most directly involved in the intervention compared with their counterparts in control schools. The effect of the intervention was, in the aggregate, more network stability across students in treatment schools as a whole. One implication is that one way in which the peer harassment intervention may have led to positive outcomes at the school level, in addition to the social influence and norm mechanisms posited by Paluck et al. (2016), was by stabilizing the social networks of those who attended treatment schools.

We can see this effect even more precisely when we examine the relationship between being in a treatment school and network stability for different populations of students in the school. As we saw above, students who themselves participated in the intervention (intervention students) in treatment schools experience an average decline in their network stability. Yet, students who nominated treatment students as someone they choose to spend time with at wave 1 who were in treatment schools—namely, those one step removed from treatment students at the beginning of the school year—experienced about 10 percent more stability in their social ties from wave 1 to wave 2 relative to similar students in control schools (i.e., those students who nominated students who *would* have been in the intervention program had the school been randomized to receive the intervention). The peers of treatment students experienced significantly more stability in their social ties over time compared with their counterparts in control schools. Finally, students in treatment schools who were not exposed to the intervention program either directly or indirectly through peers experienced an increase in the stability of their ties of about 4 percent compared with similar students in control schools, when controlling for individual characteristics.[8]

Despite instability in intervention students' networks stemming from the intervention program itself (relative to counterfactual students in control schools), which brought together students who previously did not know each other, we do not observe widespread instability among other students in treatment schools, as we might expect if network instability followed a vacancy chain model (White 1970), wherein network instability among a subgroup produced instability in other subgroups in the network. Instead, based on the evidence that indicates that the intervention stabilized the relationships of nonintervention students—whether peers of those intervention students or not—in treatment schools, we might conclude that the content of the intervention was important within these schools. The intervention program focused specifically on helping students create strong friendships and positive peer interactions, which may have encouraged network stability by promoting positive relationships in the treatment schools.

Discussion

The findings we present here have implications for scholars of social networks and scholars of social change. First, we find that social instability has a strong and negative effect on well-being and academic effort. Based on this evidence, social scientists ought to think about instability in an individual's relationships across time as a distinct social process with substantive, negative effects on well-being and other life outcomes. The effects of network instability, we find, are distinct from the effects of the number of ties an individual has, from changes in the composition of peers, and from effects due to one's network structural position. Moreover, network instability leads to negative individual-level outcomes whether it arises endogenously or exogenously.

Future work should pursue the strength of the effect of network instability on well-being across different populations and organizational conditions. We might expect these effects to be particularly strong in middle schools given the extent of turnover in relationships among adolescents and the visibility of these changes to others. On the other hand, because of the frequency of turnover in relationships among adolescents, it may be more normative, which may buffer against some of the negative consequences of network instability in a way that is not true for adults. Another potential avenue for future research is to more fully explore the sources of individual-level variation in the Jaccard index. In our analyses, treatment status and an array of individual-level variables explain only a modest amount of variation in the Jaccard index.

We also find that a successful prosocial intervention, meant to reduce peer harassment behavior within schools, incidentally created network stability in treatment schools overall. The intervention may have worked to improve student outcomes at least in part by creating the conditions within which students' ties became more stable across the school year. Interestingly, however, social stability is not evenly distributed among students. The intervention program, during which intervention students became the public face of the anti-peer harassment campaigns in their schools—by identifying key problems and devising and implementing solutions to them—succeeded in creating stability for some students but not for all. Indeed, those who participated directly in the intervention program had their networks destabilized as a result when compared with counterfactual students in control schools. And the instability the intervention students experienced as a result of the intervention program, we find, was as personally detrimental to them as the endogenous instability experienced by equivalent students in control schools.

This suggests a final potential avenue for future research. Traditional theories of collective action problems (Oliver, Marwell, and Teixeira 1985; Olson 1965) highlight the fact that, absent coercion, free riders are able to take advantage of the public goods created through collective action without incurring any of its costs. To the extent that social networks have been incorporated into theories of collective action, it has been to push back against an atomized view of individual behavior, arguing that people understand their interests and make decisions about their behaviors only in relationship to those around them, such that the problem of collective action is less of a problem than previously thought (Kim and Bearman 1997). However, in some cases, network processes might actually exacerbate collective action problems. Direct participants in collective action may be excluded from the public goods they helped create because of the instability their participation introduced into their own networks. To the extent that the dynamics here are generalizable to other cases of collective action, and that the benefits of collective action are available only to those who do not participate in it, one might imagine that, if anything, previous research has understated the difficulties of its initiation.

Notes

1 Blocks were composed to maximize balance on the following variables: the latitude and longitude location of each school; the average school population as measured by the number of students who took the prerandomization student surveys; a number of school measures from the New Jersey State Department of Education (the population in each of the grades—from fifth to eighth, depending on the school—during the year prior to the

study (2011), the racial composition of the school, the percentage of students identified as having limited English proficiency and the percentage of students receiving free or reduced lunch); and the average network clustering coefficient and network density calculated from student network data gathered in the prerandomization student surveys. Within each of the 14 school blocks, 2 schools were assigned to the control condition and 2 to the treatment condition using a random seed procedure.

2 Across treatment schools, 24 percent of selected students did not receive parental permission or did not elect to participate. Treatment students who returned their permission slip attended an average of 5.33 meetings. All analyses reported use the most conservative measure of program impact, following the Intent to Treat paradigm, where all students selected to participate in the intervention program, regardless of whether they returned their permission slip or attended regularly, are considered treatment students (Gerber and Green 2012).

3 Though the intervention was not designed to examine the effects on network stability, we did intend to examine the incidental effects of the intervention on network structure, and we included that in our preregistered analysis plan for the project (the plan has since been migrated to the Open Science Foundation repository under "Climates of Conflict: A social network driven experiment in 56 schools."

4 For a detailed comparison of the characteristics of eligible and ineligible students, see Table S2 (supplementary information) of Paluck et al. (2016)

5 We repeated this analysis using a measure of year-long grade-point average (GPA), which was measured at the end of the school year. We find the same effects for GPA as we do for self-reported academic effort. For example, a one-unit increase in the Jaccard index is associated with a 0.14 increase in GPA standard deviation; adjusted $R^2 = 0.34$. However, because the measure includes grades from earlier in the year, making it unclear whether relational change preceded GPA or vice versa, we report results for academic effort.

6 We ran a series of robustness checks for these analyses, including using other measures of changes in the behaviors and attitudes of peers. Our results are robust to using alternative measures of the characteristics and behaviors of new peers (e.g., gender, indegree, number of conflict nominations), and to using both wave 1 and wave 2 measures of the behaviors of peers or change score measures of peer behaviors. We also tested models with different combinations of these terms for the proportion of new network peers who report various behaviors: only participation in conflict, dating, or conflict attitudes for assessing well-being outcomes; only academic effort for a respondent's academic effort; subsets of these four measures; or all four measures simultaneously. These modeling choices did not affect the results. These behaviors (conflict, dating, conflict beliefs, and homework) may co-vary within individuals, so the measure of the proportion of new peers who report those behaviors are not independent of each other, but we find no evidence of multicollinearity.

7 These results are robust to other measures of network structure that might bear on well-being and academic effort, including changes in eigenvector centrality and changes in reciprocated social ties.

8 The approach we selected for this analysis, examining the effect on students who nominated treatment students as someone they spent time with at wave 1, is less precise than the strategy for identifying peer influence effects in Paluck et al. (2016), which used a smaller subset of students with equal probabilities of exposure across the treatment conditions. We selected this analytical strategy instead of following the more controlled strategy in Paluck et al. (2016; see supplemental information for details) in the interest

of examining intervention effects overall, even if some portion of the effect might be accounted for by initial differences in selection into exposure to treatment students at wave 1. The results are the same if we consider peers nominated by intervention students as well.

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