The Externality of Negative Emotion

Weina Zhou
Dalhousie University

Shun Wang (swang@kdis.ac.kr)
KDI School of Public Policy and Management https://orcid.org/0000-0001-7351-1168

Article

Keywords: mental health, schools, emotional contagion

Posted Date: July 30th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-743332/v1

Abstract

To identify the causal impact of emotional contagion, recent studies mainly rely on online or lab experiments. This paper examines the causal impact of emotional contagion among middle school students, using a nationally representative school-based survey in China. We focus on schools that randomly assign students to classrooms and isolate the variations in classmates' emotions based on a factor that originates outside the classroom: whether the classmate had a serious illness before primary school. We find that the effect of emotional contagion in a real-world setting is larger than previous findings from experimental studies have shown.

Main Text

With rising attention to the global mental health crisis in the past decade[55,95,96,97], researchers across such disciplines as economics, sociology, and medicine have become increasingly interested in emotional contagion, a phenomenon whereby one's emotion can cause others to have a similar emotion. Understanding how and to what extent one's mental state could affect that of others is important. If there is spillover, the benefits of helping an individual with negative emotions could largely outweigh the cost, and undertaking interdependent interventions could be much more effective than independent individual-intervention strategies[5].

Despite widespread public interest in understanding emotional contagion, the existing empirical knowledge is limited. Identifying the causal effect of emotional contagion has proved to be difficult because of identification issues such as self-selection, common shocks, and reflection[15,69]. Additionally, obtaining information on every individual in a specific social network is usually not feasible because of data limitations. As a result, most causal evidence on emotional contagion relies on lab or online experiments[12,19,21,31,60]. The most common face-to-face causal influences that occur in our daily lives are largely understudied by researchers[26].

This study examines the causal effects of emotional contagion among middle-school students in the classroom: whether and to what extent a student's emotion could be affected by his or her classmates' emotions. We focus on the middle school period, which is when an individual's emotional skills are thought to develop and a lifelong personality is shaped[14,27,39,55]. The main measure we use is the frequency of a negative emotion—feeling unhappy—in the previous week, taken from the China Education Panel Study (CEPS), which is the first nationally representative survey of middle school students in China. Three other negative emotions—un-joyfulness, sad, and stressed—are also examined to demonstrate the robustness of our main results. Self-reported negative emotions are often used as important measures of mental health[12]. These measures are widely used for children and youth, such as in OECD's Programme for International Student Assessment (PISA)[72] and in the Korea Children Youth Panel Survey[76].

The principle contribution of our study is to develop a strategy for estimating the causal effect of emotional contagion in a real-world setting. Our study has the following distinctive features. First, the study is able to capture a full picture of a particular social network—classmates—because once a classroom is selected for the sample in the CEPS, every student in the classroom is surveyed. Second, we address the self-selection issue at school level by controlling for school fixed effects, and address the self-selection issue at classroom level by

only including schools that randomly assign students to classrooms (about 80% of schools in the CEPS data). Third, we use novel instruments to address the issues of common shocks and reflection. Both issues arise from the fact that students study and interact daily in the same classroom; they experience the same classroom environment (such as their teacher's character or disposition) and affect each other's emotions in the classroom simultaneously. We address these issues by isolating variation in classmates' emotions that originate outside the classroom—whether the classmate had a serious illness before primary school. An individual's emotion is generally correlated with her past health condition[24,48,65,81,84]. Our data show a strong correlation between classmates' preexisting health status and their current emotion. We therefore estimate the impact of classmates' emotion that is driven by events outside the classroom on an individual's emotion. We further consider two alternative instruments that also originate outside of the classroom—whether classmates' parents have a low self-assessed health status and whether classmates have experienced parental conflict at home—to confirm the robustness of our results.

We find that a one-standard-deviation increase in a student's classmates' negative emotions causes the student's negative emotion level to increase by about one-fifth of a standard deviation. These results are supported by both a cross-sectional sample and a panel sample in which individual fixed effects and teacher fixed effects are controlled for.

The survey question that measures our primary instrumental variable (IV)—whether a student had a serious illness before primary school—is asked of both students and parents. We find that both the parent-reported measure and the student self-reported measure give similar second-stage estimates. A minor difference is that the latter is more closely correlated with the student's own emotion, and therefore yields a stronger first-stage result. On the other hand, we do not find strong evidence that a specific type of illness, such as lung or heart disease, has a stronger effect than other types of illness. However, this could be due to the limited variation across the types of illnesses reported in the data. To address concerns regarding potential measurement errors in the self-reported illness, we experiment by adding three types of measurement errors to our data using Feld-Zölitz method[30]: overreporting, underreporting, and mean-zero (classical) measurement error. Simulation results suggest that our estimates are robust to measurement errors.

Our study contributes to the literature by estimating the causal effects of emotional contagion among teenagers through real-life interaction. How to identify the effects of emotional contagion in various social contexts remains an open question in the literature. Recent studies have mainly conducted experiments using online social networks or in the laboratory, which (partially) free identification from self-selection, common shocks, and reflection issues. The laboratory experiments rely on techniques that randomly select participants into influencer or receiver groups[7]. However, the results are limited to short-term exposure (usually only several minutes) to strangers in the laboratory. Another strand of the literature analyzes the influence of posts on social network platforms (such as Facebook or Twitter), with a specific focus on adult online friendship networks[6,12,19,21,31,60]. Several limitations in the literature remain. First, it is unclear whether the problem of self-selecting into an online friendship network can be fully avoided. Second, real-life contagion could be different from interactions online or with strangers in a laboratory. Moreover, it is unclear whether emotional contagion among adolescents is similar to that among adults.

The causal effect found in this study is consistent with several studies that observe sizable and significant emotional correlation among adults[34,57] and adolescents[28,50,79,92] in real-world settings. Our study contributes to the literature on emotional contagion in various contexts[77], such as within social ties[34,82]; within communities[57,91]; among students[56], among coworkers[86,87,89,94]; and within families[78]. Our results are larger than the spillover of psychological distress among college roomates[26]. One potential reason is that middle school students are more sensitive to peers' emotions as they go through puberty. Our results also support theoretical evidence that suggests the existence of social contagion, whereby one copies others' emotions or behaviors through real-life interactions[8,42,44,45].

Our findings further contribute to the literature on the long-term impact of early childhood health conditions[2,23]. This paper provides new evidence that the impact of early childhood illness could spill over to others by affecting their mental health through close interactions. The presence of such negative spillover effects adds a social cost of an individual's early childhood illness, which so far has generally been ignored by most policymakers and researchers.

This paper is also broadly related to the literature on peer compositional effects, which study the effects of peers' gender[11,36,40,49,52,67]; ability[16,25,53,68,98]; migration status[41]; parental characteristics[10,17,18,63,100]; and smoking[58,61,62]. The paper is also closely related to the literature examining the effect of peers' behavioral or mental difficulties on students' academic achievements[1,50]. This study contributes to the peer effect literature by providing new evidence of emotional contagion.

Results

Table 1 reports baseline OLS regression results from regressing an individual's unhappiness on the average unhappiness of his/her classmates, controlling for a set of covariates. Column 1 reports the results only controlling for school and grade dummies. The coefficient of classmates' unhappiness is 0.703 and significant at the 1% level. Column 2 further controls for a set of individual characteristics and yields a smaller but still significant coefficient, 0.632. The coefficient remains essentially unchanged (0.604) when we control for teacher and classroom characteristics in column 3.

Table 1. The Correlation between Own Unhappiness and Classmates' Unhappiness (OLS Regression)

	(1)	(2)	(3)
	Dependent Variable: Own Unhappiness		
Classmates' Unhappiness	0.703***	0.632***	0.604***
	(0.024)	(0.033)	(0.036)
Age		0.013	0.011
		(0.010)	(0.010)
Female		0.073***	0.081***
		(0.021)	(0.022)
Minority		0.016	0.008
		(0.027)	(0.027)
One Child		-0.007	-0.004
		(0.020)	(0.020)
Wealth		-0.087***	-0.087***
		(0.016)	(0.016)
Father's Years of Schooling		-0.003	-0.003
		(0.003)	(0.003)
Mother's Years of Schooling		-0.007**	-0.007*
		(0.003)	(0.003)
Teacher Characteristics			
Female			-0.011
			(0.016)
Age			0.001
			(0.001)
Years of Schooling			-0.016
			(0.019)
Years of Experience			-0.001
			(0.001)
Classroom Characteristics			
Classroom Size			0.001
			(0.001)

Percentage of Female			-0.209***
			(0.078)
School & Grade FE	Yes	Yes	Yes
Observations	12,677	11,805	11,670
R-squared	0.038	0.046	0.046

Notes: CEPS 2013 sample is used. OLS estimates are reported. Standard errors are clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1.

As discussed in the empirical strategy section, the OLS regressions are likely to contain both positive and negative direction of bias. We thus adopt the IV approach to estimate the model. The second-stage and first-stage estimates are reported in Panels A and B of Table 2, respectively. Classmates' self-reported illness are used as the IV. In Panel A, the coefficient of classmates' unhappiness in column 1, controlling only for school and grade fixed effects, is 0.78. The estimate is slightly reduced as we introduce more controls in columns 2-4, and all are statistically significant at the 1% level. The point estimate in column 4 (with a full set of controls) is 0.654, which suggests that a student's unhappiness measure increases by 0.654 (on the 5-point scale) if all of her classmates become 1 point less happy. Assessing the magnitude in terms of standard deviation, this means that a one standard deviation increase in peers' unhappiness causes the individual's unhappiness to increase by 0.182 (=0.29*0.654/1.04) standard deviation.

Table 2. The Effect of Classmates' Unhappiness on Own Unhappiness, Using Illness before Primary Schooling as IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable (panel A): Own Unhappiness						
Panel A. 2SLS Estimates							
Classmates' Unhappiness	0.780***	0.705***	0.704***	0.654***	0.813***	0.714***	0.759***
	(0.068)	(0.120)	(0.118)	(0.147)	(0.136)	(0.128)	(0.142)
Weak IV Robust 95% CI	[0.665, 0.912]	[0.469,0.941]	[0.473, 0.934]	[0.365, 0.942]	[0.536, 1.093]	[0.462, 0.965]	[0.484, 1.081]
	Dependent Variable (panel B): Classmates' Unhappiness						
Panel B. First Stage Estimates							
Classmates' Illness	1.118***	0.972***	0.973***	0.895***	0.922***	0.930***	0.892***
	(0.261)	(0.287)	(0.279)	(0.278)	(0.271)	(0.285)	(0.270)
Kleibergen-Paap *F*-statistic	18.354	11.441	12.163	10.384	11.573	10.673	11.445
	Dependent Variable (panel C): Own Unhappiness						
Panel C. Reduced Form Estimates							
Classmates' Illness	0.871***	0.685**	0.685**	0.586*	0.749**	0.664**	0.623**
	(0.269)	(0.305)	(0.296)	(0.301)	(0.299)	(0.305)	(0.300)
Controls (for all panels)							
School & Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Characteristics		Yes	Yes	Yes	Yes	Yes	Yes
Classroom Characteristics			Yes	Yes	Yes	Yes	Yes
Teacher Characteristics				Yes	Yes	Yes	Yes

Classmates' Family Background						Yes	Yes
Classmates' Current Health							Yes
Observations (for all panels)	12,541	11,683	11,683	11,548	9,904	11,003	9,720

Notes: CEPS 2013 sample is used. 2SLS estimates are reported in Panel A. OLS estimates are reported in Panel B. Panel C reports the reduced form estimates. Classmates' Illness is defined as percentage of classmates had serious illness before primary schooling (reported by classmates). Column 5 excludes individuals reported having serious illness before primary schooling. Individual characteristics: age, gender, minority, one child, family wealth level, father's education, mother's education, grade 9 dummy. Classroom characteristics: classroom size, percentage of female in the classroom. Teacher characteristics: age, gender, education and experience of the head teacher. Classmates' family background: mother's education, father's education, family wealth before primary schooling, current family wealth. Classmates' current health: self-evaluated current health condition, hospitalization in the past 12 months and BMI. Standard errors are clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1.

The first-stage estimates in panel B of Table 2 show that the correlation between the instrument and the average of classmates' unhappiness is positive and statistically significant at the 1% level. The point estimate is close to one, which suggests that if all classmates had a serious illness before primary school, classmates' average unhappiness would increase by almost one point. The Kleibergen-Paap *F*-statistic for the excluded instrument is larger than 10 in all columns. Thus, it is very unlikely that our estimates are biased by weak instruments. We nevertheless report the weak IV robust 95% confidence interval of our Two-Stage least squares (2SLS) estimates in square brackets. We consider both the Anderson-Rubin method[3] and the Kleibergen–Moreira Lagrange Multiplier (LM) method[57,70] to compute the confidence interval (CI). Results are very similar. We thus report the widely used Anderson-Rubin CI in the table. The grid search in Anderson-Rubin method[3] could result in an empty CI. In such case, LM CI is reported. Our results show that all of the confidence intervals exclude zero. We thus conclude that our results are robust.

There is a potential problem in estimating peer-effects models, caused by a mechanical negative correlation between own and average peer characteristics[4,43], in our case, between own illness and average classmates' illness. The solution to this problem is to distinguish between the individuals who are being affected and the individuals who are affecting their peers, if such a distinction is possible. Following the literature[5,18,54], we restrict our sample to students who did not have a serious illness before primary school in column 5 of Table 2. The coefficient is 0.806 and significant at the 1% level, which is very similar to the result in column 4. Our results, therefore, are robust to the sample restriction.

One concern regarding using classmates' early childhood illness as the IV for classmates' emotion is that classmates' health status is likely to be correlated with classmates' other family characteristics, such as family wealth or genes (the exclusion restriction). Note that since classrooms are randomly assigned (verified in the next section), classmates' family characteristics are likely to be exogenous variations with regard to students in the class: Whether the assigned class has more classmates who are wealthy or have healthy genes are idiosyncratic variations. To test the robustness of the results, column 6 adds the following classmates'

characteristics to our baseline estimation in column 4: classmates' mother's education, father's education, family wealth before primary schooling, and current family wealth. As expected, the 2SLS estimate remains essentially unchanged (0.714***). Although it is impossible to control for all classmates' family background characteristics, they are unlikely to change the estimates substantially.

Some may concern that a student's past health condition could affect peers' emotion not through emotion contagion, but through other channels such as current health condition. For example, peers may worry about the student's health condition and become stressed and sad; a currently unhealthy condition may cause a student to withdraw from social activities, which could make peers feel unhappy. To address this concern, we control for a set of variables measuring students' current health condition. The first variable is parent responses to the survey question "how is your child's current health condition" on a scale from 1 (very bad) to 5 (very good). The second variable is students' responses to whether they have been hospitalized in the past 12 months. The third variable is students' current BMI. We calculate the classmates' average for each of these three variables to measure classmates' current health condition. Column 7 of Table 2 reports the regression results controlling for all three variables. The 2SLS estimate is almost unchanged (0.736) and maintain the significance level at the 1 percent.

The size of the 2SLS estimate is just slightly larger than the OLS result, 0.654 vs 0.604, and the difference is not statistically significant. This does not mean that the OLS estimates are not biased, since the biases could be either positive or negative. For example, simultaneity causes a positive bias, and attenuation bias—induced by measurement errors in the happiness measure, which drive the estimates toward zero—causes a negative bias. Instead, the statistically indifference between the 2SLS and OLS estimate might indicate that the various types of biases in the OLS estimates are largely cancelled out by each other.

Our results are much larger compared with findings based on online social networks or laboratory experiments, suggesting contagion through face-to-face interactions is stronger than online interactions. For example, a reduction in posts by online friends that contain positive or negative emotions reduces own positive or negative posts by at most 0.1 percent[60]. Note that all the experimental studies examine the outcomes of adults, therefore, the differences in the size of the effect could also be driven by age differences: Middle-school age is a period where one's noncognitive outcomes are easily affected by surrounding environment and lifelong characters are largely shaped[14, 22,27,46]. One study shows that class-level well-being is positively associated with students' subsequent well-being in Filipino by controlling for both prior well-being and key demographic variables[56], though concerns over common shocks remain. Different from the literature which does not find peer effect on mental health also using CEPS data[99], this paper uses variation in peers' mental outcomes that is completely originates outside of the classroom, and therefore is able to better address the common shock and simultaneous causality issue.

Robustness

We report the reduced-form results in Panel C of Table 2 to show that the IV, classmates' illness, has a direct positive effect on own unhappiness. The point estimates are all statistically significant at the 5% level. The results add to our confidence in the validity of our IV. Further experiments to confirm the validity of our method

and the robustness of our results are reported in the Supplementary Information file. The followings are the summary of the experiments.

We first test the exogeneity of the IV by carrying out a balance test, which does not find that individual and teacher characteristics are jointly correlated with the IV (Table S1). We then re-estimate our main results by only using first year students, since reassignment in the first year is less likely. Our results are robust (Table S2). We next conduct two falsification tests to verify the identification assumption: We reassign the instrument to another class in the same school and find no relationship between a falsely assigned instrument and individual's emotion (Table S3); we also find the instrumented classmates' unhappiness have no effect on predetermined characteristics (Table S3).

We also find consistent results by using parent-reported measures of illness as the IV (Table S4) and specific type of illness as the IV (Table S5), and alternative measures of negative emotions (Table S6). We further confirm that our results are robust to measurement error by randomly introducing more measurement errors to our data (Figure S1). Lastly we exploit the panel data, using alternative IVs and controlling for teacher fixed effects. We still find consistent results (Table S7).

Discussion

After the family, schools are the most important environments in adolescents' lives, and thus it is crucial that we understand how students may affect each other. This study explores the spillover effects of emotions among students, and finds that the negative emotion of a student's classmates could cause the student to also experience a negative emotion. In other words, there is strong negative externality of one student's negative emotion on classmates. The size is fairly large: almost one-fifth of a standard deviation.

We are able to avoid the self-selection problem by exploiting the nature of randomly assigning students to different classrooms. In addition, we used students' preexisting health characteristics (whether having been seriously ill before entering primary school) as the main IV for students' happiness to address potential endogeneity. We thus identify the peer effect of a negative emotion among middle school students. Our findings are robust to various measures of negative emotions. In addition, we show that the emotional contagion could be caused by other exogenous variations from outside the classroom, such as parental conflict at home and parental health issues.

The presence of the externality of negative emotions in daily life may exacerbate children's emotional or behavioral distress; this is prevalent in many countries, as shown by the OECD's PISA[72]. The results of this paper underscore the importance of assessing each child's mental health and addressing problems before they spill over to others.

Our research context, in which students are randomly placed together, is particularly important for estimating spillover effects and thereby motivates policy interventions. We cannot expect middle school students to consider the potential negative impact on others and, in turn, mitigate negative spillovers. External intervention (e.g., through consultation with experts in this area) is therefore necessary to correct market failures.

Our findings imply that, to the extent of the strong spillover effect of negative emotions among classmates, the positive externalities from prevention and intervention would be especially large. In other words, providing interventions for students who are experiencing negative emotion will not only improve their own mental status but also the mental status of their classmates, which enhances the efficacy and cost effectiveness of the intervention. Similar to treating an infectious disease such as COVID-19, interventions that target socially connected individuals simultaneously could be more effective for reducing a negative spillover effect than individual interventions implemented at different times.

Methods

Data source

The main data set used in this paper is the China Education Panel Study (CEPS) 2013, which is a school-based study. It covers both rural and urban areas in mainland China and is a nationally representative survey that applies a stratified, multistage sampling design with probability proportional to size. The CEPS has a unique feature whereby once a classroom is selected for the sample, all students attending the class and their parents are surveyed. This key feature allows us to obtain a full picture of classmates' emotion. The CEPS 2013 surveys students who were in grade 7 and grade 9 during the 2013 academic year. The academic year in China starts in September and ends in June of the following year. Students in grade 7 are generally 12-13 years old.

In addition to the 2013 wave, the CEPS also conducted a follow-up survey in 2014. The 2014 wave followed the students who were grade 7 in the 2013 wave and became grade 8 in 2014. The CEPS 2014 is used as a supplementary dataset in our analysis. This is because several key variables either did not change over time (such as our main IV, illness before primary school) or were not surveyed in the 2014 wave (such as our alternative IV, parental health outcome). Hence, we cannot use the panel feature in the regression analysis using these variables. We will, however, use the panel feature in Section 4.4, in which parental conflict is used as an alternative IV.

All school-age children in China are entitled to a free and compulsory 9-year education by law. Grade 7 is the first year of middle school education and Grade 9 is the last year. Most middle schools and primary schools in China are public schools (93% of sample schools are public in CEPS), and students are assigned to public schools based on their residence location. Typically, students come to class in the morning and take all courses with the same classmates in the classroom throughout the day. Classrooms are usually fixed through an academic year, and students interact frequently within a classroom.

Regression samples

Most Chinese middle schools randomly assign students to classrooms at the beginning of the 7th grade, and many of them keep the assignment through the 9th grade, to ensure equal and fair educational opportunities at the level of compulsory education. We focus on schools that randomly assign students at the beginning of grade 7 and no reassignment is made in grade 8 or grade 9 in the 2013 academic year. There are in total 109 schools recorded in the CEPS 2013 data. According to the school principal survey of the CEPS, 93 schools report that they apply a random class assignment policy to grade 7 students. Of these 93 schools, 78 reported that they did not rearrange classrooms for grade 8 and grade 9. We also drop one school that only had one

classroom in the sample, because we cannot carry out the within-school comparison in a school with only one classroom. Based on these criteria, the cross-sectional sample consists of 12,677 students in 301 classrooms in 77 schools. Each school has two to four classrooms.

Variables and summary statistics

Negative emotion

Table 3 reports summary statistics of variables used in the sample. Our main outcome variable is a negative emotion: *unhappiness*. It is measured by the following survey question: “Did you feel unhappy in the last seven days?” Answers are rated on a 5-point Likert scale (1=*never*, 2=*seldom*, 3=*sometimes*, 4=*often*, 5=*always*). More than 50% of the students reported either “seldom” or “sometimes” feeling unhappy. The mean of individual-level unhappiness is 2.31, with a standard deviation of 1.04; the mean of classmates’ unhappiness is the same as that of the individual level, 2.31, with a smaller standard deviation of 0.29. The distribution of these two variables is presented in Figure 1. In addition to *unhappiness*, the survey also asked the same questions for three similar negative emotions: “not joyful,” “sad,” and “stressed.” We present the regression analysis for *unhappiness* in the main results and report the regressions for other negative emotions in the robustness checks reported in the Supplementary Information file (Table S6).

Table 3. Summary Statistics

Variable	Mean	SD
Individual Characteristics		
Unhappiness	2.31	1.04
Illness	0.14	0.35
Parental Conflict	0.10	0.30
Parental Health	3.85	0.91
Wealth	3.01	0.55
Age	13.95	1.36
Female	0.48	0.50
Minority	0.12	0.32
One Child	0.46	0.50
Grade 9	0.46	0.50
Father's Years of Schooling	10.23	3.52
Mother's Years of Schooling	9.50	3.84
Peer Characteristics		
Classmates' Unhappiness	2.31	0.29
Classmates' Illness	0.14	0.08
Classmates' Parental Conflict	0.10	0.06
Classmates' Parental Health	3.85	0.29
Classroom Characteristics		
Classroom Size	47.57	13.78
Percentage of Female	0.48	0.09
Teacher Characteristics		
Female	0.63	0.48
Age	37.02	7.52
Years of Schooling	15.93	0.46
Years of Experience	15.92	8.09
Observations	12,677	
Number of Classrooms	301	
Number of Schools	77	

Data: CEPS 2013.

Illness

The variable illness is measured using the following survey question in the CEPS's 2013 wave: "Did you have a serious illness before you started elementary school?" About 14% of students answered "Yes," with a standard deviation of 0.08. Figure 2 presents the distribution of the proportion of students who answered "Yes" per classroom. Our alternative measure of illness uses a similar survey question, which is answered by students' parents in the parent survey of the CEPS 2013: "Did your child have a serious illness before the child started elementary school?" About 9% of parents in the sample answered "Yes," with a standard deviation of 0.08. The parent-reported measure of illness is smaller than the student's self-reported illness. This is likely to be caused by parents' and children's different definitions of serious illness. Children may also have different perceptions of some illnesses compared with their parents. We find that compared with the parent-reported measure, the student self-reported measure is more closely correlated with the student's own emotion, and therefore yields a stronger first-stage result (Table 2 vs Table S4).

A slightly different question regarding children' illness is posed in the CEPS's parent survey in 2014. The survey asks parents to report whether their children had the following types of serious illness and, if so, when the child had it: heart, brain, limb, kidney and lung. In total, 4.2% of parents reported that their child had at least one of these diseases before age 7: heart (0.3%); brain (0.2%); limb (2.1%); kidney (0.2%); and lung (1.9%).

Control variables

Of the student characteristics, family wealth is measured using students' self-reported family financial conditions on a 5-point scale that ranges from 1=*very poor* to 5=*very rich*. Students are on average 14 years old; 48% are female; 12% are minorities; 46% are *One Child,* meaning that they don't have siblings; 46% are in grade 9; and 54% are in grade 7 (Table 4). Respondents' fathers have on average 10.23 years of education, and mothers have 9.5 years. On average, each classroom has 47 students and 48% are female. Teachers on average are 37 years old; have about 16 years of education and 16 years of experience; and 63% of teachers are female.

Empirical strategy

The main difficulties in identifying the causal effect of peers' emotion on an individual's emotion are self-selection, common shocks, and the reflection issue. Self-selection (also called "sorting" or "homophily") is the tendency of like to attract like: In the case of school children, we might observe that both a student and her classmates are happy only as a result of sorting. For example, students (or their parents) who care more about their well-being may self-select into a school or classroom in which most students are well-behaved and interact in a friendly manner. The common shocks issue (also called "contextual effects") arises because individuals and their social contacts are affected by a common environment. The common environment for school children could be their teacher's character or disposition. Hence, individuals' emotions could be correlated even without one affecting another. The *size* of the causal effect of social influence is

difficult to identify, because individuals simultaneously affect each other; this problem is called the reflection issue[69]. In this section, we describe our empirical strategy for addressing each.

To address the self-selection issue, we restrict our sample to schools in which students are randomly assigned to classrooms in grade 7—the first year of middle school—and no further reassignment is made in grades 8 or 9. School fixed effects control for preexisting factors that could affect selection into a school or community. The fixed effects also control for school- or neighborhood-level environmental factors that may cause overall differences in emotions across schools or neighborhoods.

Both the reflection issue and the common environment issue arise from the fact that students study and interact in the same classroom on a daily basis. Thus, we address these challenges by isolating the variation in classmates' emotions that is not determined in the classroom. Specifically, we instrument classmates' emotions using classmates' early childhood health condition—i.e., serious illness before primary school.

Whether classmates had a serious illness before primary school is very likely to be an exogenous variation; illness in the past cannot be affected by the current classroom environment or current classmates' characteristics. Furthermore, one's illness before primary school could potentially affect one's own emotion. An individual's emotion is generally correlated with her health condition[48,65,73,74,81]. A serious disease in childhood could potentially have long-term consequences on her current emotions[24,84]. Thus, we can expect a certain amount of variation in classmates' emotion that is driven by their average early childhood health conditions. Our data support this conjecture. As shown in Figure 3, we find a strong positive correlation between the IV (the average incidence of classmates' illness) and the endogenous variable of interest (classmates' average emotion). In the figure, we divide our sample into three equal groups based on the proportion of classmates who had a serious illness before primary school: low, medium, and high. The figure suggests that the high group—i.e., classes where more classmates had serious illness—are more likely to report unhappy compared to the low group.

Equation (1) is the second stage of our 2SLS system and Equation (2) is the first stage.

$$E_{icgs} = \alpha \bar{E}_{(-i)cgs} + \beta StudentChars_{icgs} + \gamma ClassCharas_{cgs} + \sigma_g + \mu_s + u_{icgs}, \quad (1)$$

$$\bar{E}_{(-i)cgs} = \rho \overline{Illness}_{(-i)cgs} + \beta StudentChars_{icgs} + \gamma ClassCharas_{cgs} + \sigma_g + \mu_s + v_{icgs} (2)$$

E_{icgs} is the emotion of student *i* in classroom *c* of grade *g* in school *s*. It is constructed based on whether a student was unhappy in the previous 7 days (see Section 2.3.1). $\bar{E}_{(-i)cgs}$ is the endogenous variable of interest, the average emotion of student *i*'s classmates. Specifically, it is defined as $\bar{E}_{(-i)cgs} = \frac{\sum_{k \neq i} E_{kcgs}}{N_{cgs}-1}$, where E_{kcgs} is student *k*'s emotion and N_{cgs} is the number of students in the classroom. $StudentChars_{icgs}$ is a vector of student *i*'s characteristics. $ClassCharas_{ct}$ is a vector of classroom controls such as classroom size and teacher's characteristics. Our instrument, $\overline{Illness}_{(-i)cgs}$, denotes the proportion of classmates who had a serious illness before primary school, given by $\frac{\sum_{k \neq i} Illness_{kgs}}{N_{cgs}-1}$. σ_g and μ_s represent grade fixed effects and school fixed effects, respectively. Note that the identification strategy does not rely on within-school across-cohort variation because we draw variation from randomly assigned classrooms within schools. Despite so, our results are robust to including school×grade fixed effects. Error terms are clustered at school level to allow for within-school correlation.

Our parameter of interest, α, represents the causal effect of student i's classmates' average emotion on i's emotion. A positive coefficient, α>0, indicates that classmates who are unhappy causes a student in the same classroom to also become unhappy.

The identification strategy relies on idiosyncratic variation in the underlying health conditions across classes in the same school generated by within-school random class assignment; some classes will simply have a greater share of students who had a serious illness in early childhood than other classes. The randomly assigned composition of classrooms therefore may cause a student to have more or less negative emotion than a student in another classroom.

The identification strategy will be invalid if schools sort students based on their observed characteristics (even though schools reported that classroom assignments were made randomly) or, in a very unlikely scenario, an early childhood illness could be somehow affected by a factor in the current classroom. These identification assumptions are verified as shown in Tables S1 and S2.

The IV identifies a “local” effect: one’s negative emotion that is specifically caused by a classmate’s early childhood health condition. To show that emotional contagion could be caused by various exogenous shocks, we further exploit two alternative IVs that also stem from shocks outside the classroom (classmates’ parental conflict at home and classmates’ parental health condition) and yield consistent results as reported in Tables S7.

Declarations

Data Availability

The data used in this study are available at: http://ceps.ruc.edu.cn/English/Home.htm

Code Availability

Code is available upon request.

Acknowledgements

Wang gratefully acknowledges financial support from the KDI School of Public Policy and Management.

Author Contributions

W.Z. did the research design, analyzed the data, and wrote the paper.

S.W. did the research design, analyzed the data, and wrote the paper.

Competing Interests

The authors declare that they have no competing interests.

References

1. Aizer, A. (2008). Peer effects and human capital accumulation: The externalities of ADD (No. w14354). National Bureau of Economic Research.
2. Almond, D., Currie, J., & Duque, V. (2018). Childhood circumstances and adult outcomes: Act II. *Journal of Economic Literature*, 56(4), 1360–1446.
3. Anderson, T. W., & Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics*, 20(1), 46–63.
4. Angrist, J. 2014. The perils of peer effects. *Labour Economics*, 30(C): 98–108.
5. Angrist, J., & Lang, K. (2004). Does school integration generate peer effects? Evidence from Boston’s Metco Program. *American Economic Review*, 94(5), 1613–1634.
6. Aral, S., & Nicolaides, C. (2017). Exercise contagion in a global social network. *Nature Communications*, *8*(1), 1–8.
7. Aral, S., & Walker, D. (2012). Identifying influential and susceptible members of social networks. *Science*, *337*(6092), 337–341.

8. Barsade, S. G. (2002). The Ripple Effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, 47(4), 644–675.
9. Bertrand, M., Luttmer, E. & Mullainathan, S. (2000). Network effects and welfare cultures. *Quarterly Journal of Economics*, 115(3), 1019–1055.
10. Bifulco, R., Fletcher, J. M., & Ross, S. L. (2011). The effect of classmate characteristics on post-secondary outcomes: Evidence from the Add Health. *American Economic Journal: Economic Policy*, *3*(1), 25–53.
11. Black, S. E., Devereux, P. J., & Salvanes, K. G. (2013). Under pressure? The effect of peers on outcomes of young adults. *Journal of Labor Economics*, *31*(1), 119–153.
12. Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*(7415), 295–298.
13. Bor, J., Venkataramani, A. S., Williams, D. R., & Tsai, A. C. (2018). Police killings and their spillover effects on the mental health of black Americans: a population-based, quasi-experimental study. *The Lancet*, 392(10144), 302–310.
14. Borghans, L., Duckworth, A. L., Heckman, J. J., & Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of Human Resources*, 43(4), 972–1059.
15. Bramoullé, Y., Djebbari, H., & Fortin, B. (2020). Peer effects in networks: A survey. *Annual Review of Economics*, 12, 603–629.
16. Burke, M. A., & Sass, T. R. (2013). Classroom peer effects and student achievement. *Journal of Labor Economics*, *31*(1), 51–82.
17. Carrell, S. E., & Hoekstra, M. L. (2010). Externalities in the classroom: How children exposed to domestic violence affect everyone's kids. *American Economic Journal: Applied Economics*, *2*(1), 211–228.
18. Carrell, S. E., Hoekstra, M., & Kuka, E. (2018). The long-run effects of disruptive peers. *American Economic Review*, *108*(11), 3377–3415.
19. Centola, D. (2010). The spread of behavior in an online social network experiment. *Science*, *329*(5996), 1194–1197.
20. Christakis, N. A., & Fowler, J. H. (2008). The collective dynamics of smoking in a large social network. *New England Journal of Medicine*, *358*(21), 2249–2258.
21. Coviello, L., Sohn, Y., Kramer, A. D., Marlow, C., Franceschetti, M., Christakis, N. A., & Fowler, J. H. (2014). Detecting emotional contagion in massive social networks. *PLoS One*, 9(3): e90315.
22. Cunha, F., & Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2), 31–47.
23. Currie, J., & Vogl, T. (2013). Early-life health and adult circumstance in developing countries. *Annual Review of Economics*, 5(1), 1–36.
24. Deindl, C. (2013). The influence of living conditions in early life on life satisfaction in old age. *Advances in Life Course Research*, 18(1): 107–114.
25. Duflo, E., Dupas, P., & Kremer, M. (2011). Peer effects, teacher incentives, and the impact of tracking: evidence from a randomized evaluation in Kenya. *American Economic Review*, 101(5), 1739–1774.
26. Eisenberg D., Golberstein, E., Whitlock, J. L., and Downs, M. F. (2013). Social contagion of mental health: Evidence from college roommates. *Health Economics*, 22(8): 965–986.

27. Elango, S., García, J. L., Heckman, J. J., & Hojman, A. (2016). Early childhood education, in Moffitt, R. A. (Eds.). *Economics of Means-Tested Transfer Programs in the United States, Volume 2* (pp. 235–297), University of Chicago Press.
28. Eyre, R. W., House, T., Hill, E. M., and Griffiths, F. E. (2017). Spreading of components of mood in adolescent social networks. *Royal Society Open Science*, 4, 170336.
29. Evans, T. M., Bira, L., Gastelum, J. B., Weiss, L. T., & Vanderford, N. L. (2018). Evidence for a mental health crisis in graduate education. *Nature Biotechnology*, *36*(3), 282–284.
30. Feld, J., & Zölitz, U. (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labor Economics*, 35(2), 387–428.
31. Ferrara, E., & Yang, Z. (2015). Measuring emotional contagion in social media. *PLoS One*, 10(1), e0142390.
32. Figlio, D. N. (2007). Boys named Sue: Disruptive children and their peers. *Education Finance and Policy*, *2*(4), 376–394.
33. Fowler, J. H. (2014). Detecting emotional contagion in massive social networks. *PLoS One*, 9(3): e90315.
34. Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *British Medical Journal*, 337: a2338.
35. Gaviria, A., & Raphael, S. (2001). School-based peer effects and juvenile behavior. *Review of Economics and Statistics*, *83*(2), 257–268.
36. Getik, D., & Meier, A. N. (2020). Peer gender and mental health. WWZ Working Paper 2020/15.
37. Glaeser, E. L., Sacerdote, B., & Scheinkman, J. A. (1996). Crime and social interactions. *Quarterly Journal of Economics*, 111(2): 507–548.
38. Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881.
39. Gong, J, Lu, Y., & Song, H. (2018). The effect of teacher gender on student's academic and noncognitive outcomes. *Journal of Labor Economics*, 36(3), 743–778.
40. Gong, J., Lu, Y., & Song, H. (2019). Gender peer effects on students' academic and noncognitive outcomes: Evidence and mechanisms. *Journal of Human Resources*, 0918–9736.
41. Gould, E. D., Lavy, V., & Daniele Paserman, M. (2009). Does immigration affect the long-term educational outcomes of natives? Quasi-experimental evidence. *The Economic Journal*, *119*(540), 1243–1269.
42. Gump, B. B., & Kulik, J. A. (1997). Stress, affiliation, and emotional contagion. *Journal of Personality and Social Psychology*, 72, 305–319.
43. Guryan, J., Kroft, K., & Notowidigdo, M. J. (2009). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics*, 1(4), 34–68.
44. Hatfield, E., Cacioppo, J., & Rapson, R. L. (1993). Emotional contagion. *Current Directions in Psychological Science*, 2, 96–99.
45. Hatfield, E., Cacioppo, J., & Rapson, R. L. (1994). *Emotional contagion*. New York: Cambridge University Press.

46. Heckman, J. J., & Kautz, T. (2014). Fostering and measuring skills: Interventions that improve character and cognition. In J. J. Heckman, J. E. Humphries, & T. Kautz (Eds.). *The myth of achievement tests: The GED and the role of character in American life* (pp. 341–430). University of Chicago Press.
47. Heckman, J. J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review*, 91(2), 145–149.
48. Helliwell, J. F., & Wang, S. (2013). World happiness: trends, differences, and explanations. In Helliwell, J. F., R. Layard, & J. Sachs (Eds.). *World Happiness Report 2013* (pp. 8–37), New York: UN Sustainable Development Solutions Network.
49. Hill, A. J. (2015). The girl next door: The effect of opposite gender friends on high school achievement. *American Economic Journal: Applied Economics*, *7*(3), 147–177.
50. Hill, E. M., Griffiths, F. E., & House, T. (2015). Spreading of healthy mood in adolescent social networks. *Proceedings of the Royal Society B: Biological Sciences*, 282(1813): 20151180.
51. Horoi, I., & Ost, B. (2015). Disruptive peers and the estimation of teacher value added. *Economics of Education Review*, *49*, 180–192.
52. Hoxby, C. (2000). *Peer effects in the classroom: Learning from gender and race variation* (No. w7867). National Bureau of Economic Research.
53. Huang, B., & Zhu, R. (2020). Peer effects of low-ability students in the classroom: evidence from China's middle schools. *Journal of Population Economics*, *33*, 1343–1380.
54. Imberman, S. A., Kugler, A. D., & Sacerdote, B. I. (2012). Katrina's children: Evidence on the structure of peer effects from hurricane evacuees. *American Economic Review*, 102(5), 2048–2082.
55. James, S. L., Abate, D., Abate, K. H., Abay, S. M., Abbafati, C., Abbasi, N., ... & Briggs, A. M. (2018). Global, regional, and national incidence, prevalence, and years lived with disability for 354 diseases and injuries for 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *The Lancet*, *392*(10159), 1789–1858.
56. King, R. B., and Datu, J. A. (2017). Happy classes make happy students: Classmates' well-being predicts individual student well-being. *Journal of School Psychology*, 65, 116–128.
57. Kleibergen, F. (2007). Generalizing weak instrument robust IV statistics towards multiple parameters, unrestricted covariance matrices and identification statistics. *Journal of Econometrics*, 139(1), 181–216.
58. Knight, J., & Gunatilaka, R. (2017). Is Happiness Infectious? *Scottish Journal of Political Economy*, 64(1), 1–24.
59. Kooreman, P. (2007). Time, money, peers, and parents; some data and theories on teenage behavior. *Journal of Population Economics*, *20*(1), 9–33.
60. Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences of the United States of America*, 111(24), 8788–8790.
61. Krauth, B. V. (2005). Peer effects and selection effects on smoking among Canadian youth. *Canadian Journal of Economics*, *38*(3), 735–757.
62. Krauth, B. V. (2007). Peer and selection effects on youth smoking in California. *Journal of Business & Economic Statistics*, 25(3), 288–298.

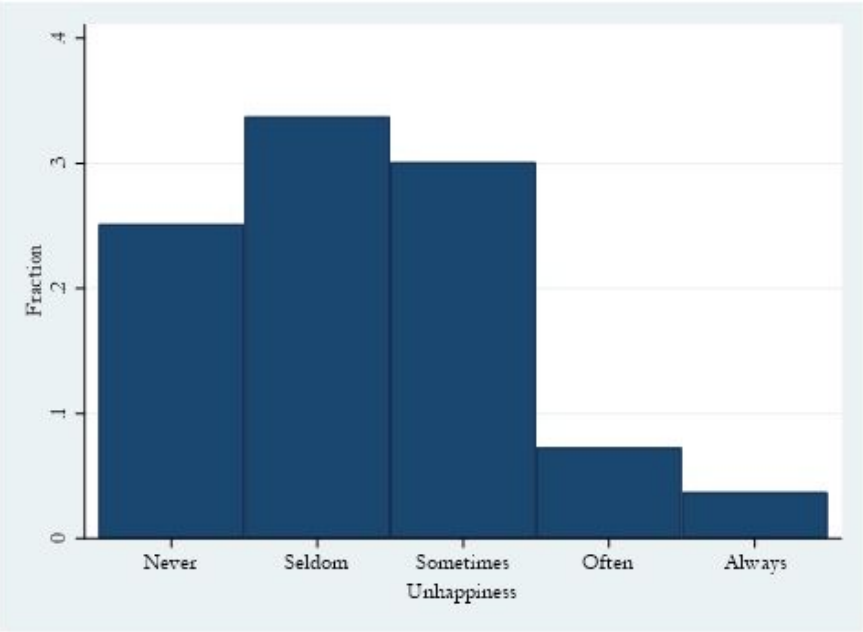
63. Kristoffersen, J. H. G., Krægpøth, M. V., Nielsen, H. S., & Simonsen, M. (2015). Disruptive school peers and student outcomes. *Economics of Education Review*, *45*, 1–13.
64. Larson, R. W., & Sheeber, L. B. (2008). The daily emotional experience of adolescents: are adolescents more emotional, why, and how is that related to depression? In Allen, N. B., & L. B. Sheeber (Eds.), *Adolescent Emotional Development and the Emergence of Depressive Disorders* (pp. 11–32), Cambridge University Press.
65. Layard, R., Chisholm, D., Patel, V., & Saxena, S. (2013). Mental illness and unhappiness. In Helliwell, J. F., R. Layard, & J. Sachs (Eds.). *World Happiness Report 2013* (pp. 38–53), New York: UN Sustainable Development Solutions Network.
66. Lavy, V., Paserman, M. D., & Schlosser, A. (2012a). Inside the black box of ability peer effects: Evidence from variation in the proportion of low achievers in the classroom. *The Economic Journal*, *122*(559), 208–237.
67. Lavy, V., & Schlosser, A. (2011). Mechanisms and impacts of gender peer effects at school. *American Economic Journal: Applied Economics*, *3*(2), 1–33.
68. Lavy, V., Silva, O., & Weinhardt, F. (2012). The good, the bad, and the average: Evidence on ability peer effects in schools. *Journal of Labor Economics*, *30*(2), 367–414.
69. Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, 60, 531–542.
70. Moreira, M. J. (2003). A conditional likelihood ratio test for structural models. *Econometrica*, 71(4), 1027–1048.
71. Neidell, M., & Waldfogel, J. (2010). Cognitive and noncognitive peer effects in early education. *The Review of Economics and Statistics*, 92(3), 562–576.
72. OECD. (2017). *PISA 2015 results (Volume III): Students' well-being*, PISA, OECD Publishing, Paris.
73. Ohrnberger, J., Fichera, E., & Sutton, M. (2017a). The relationship between physical and mental health: A mediation analysis. *Social Science & Medicine*, 195, 42–49.
74. Ohrnberger, J., Fichera, E., & Sutton, M. (2017b). The dynamics of physical and mental health in the older population. *Journal of the Economics of Ageing*, 9, 52–62.
75. Ozier, O. (2018). Exploiting externalities to estimate the long-term effects of early childhood deworming. *American Economic Journal: Applied Economics*, 10(3), 235–262.
76. Park, K., & Wang, S (2019). Youth activities and children's subjective well-being in Korea. *Journal of Happiness Studies*, 20(7), 2351–2365.
77. Povey, R. (2015). The welfare economics of infectious happiness. *Economics Letters*, 133(C), 1–3.
78. Powdthavee, N. (2009). I can't smile without you: Spousal correlation in life satisfaction, *Journal of Economic Psychology*, 30(4): 675–689.
79. Prinstein, M. J. (2007). Moderators of peer contagion: a longitudinal examination of depression socialization between adolescents and their best friends. *Journal of Clinical Child & Adolescent Psychology*, 36(2), 159–170.
80. Pugh, S. D. (2001). Service with a smile: Emotional contagion in the service encounter. *Academy of Management Journal*, 44(5): 1018–1027.

81. Reulbach, U., O'Dowd, T, McCrory, C., & Layte, R. (2010). Chronic illness and emotional and behavioural strengths and difficulties in Irish children. *Journal of Epidemiology and Community Health*, 64(Suppl 1): A4.
82. Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social networks determinants of depression. *Molecular Psychiatry*, 16: 273–281.
83. Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *Quarterly Journal of Economics*, 116 (2): 681–704.
84. Stafford, M., Gale, C. R., Mishra, G., Richards, M., Black, S., & Kuh, D. L. (2015). Childhood environment and mental wellbeing at age 60-64 years: prospective evidence from the MRC National Survey of Health and Development. *PLoS One*, 10(6): e0126683.
85. Stock, J., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In Andrews, D. W. K., & J. H. Stock (Eds.). *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press, New York.
86. Tee, E. Y. J. (2015). The emotional link: Leadership and the role of implicit and explicit emotional contagion processes across multiple organizational levels. *The Leadership Quarterly*, 26(4), 654–670.
87. Totterdell, P. (2000). Catching moods and hitting runs: Mood linkage and subjective performance in professional sport teams. *Journal of Applied Psychology*, 85(6), 848–859.
88. Totterdell, P. (2012). Are moods contagious? In P. Totterdell, & K. Niven (Eds.), Should I strap a battery to my head? (And other questions about emotion) (pp. 219–228). CreateSpace.
89. Totterdell, P., Kellett, S., Teuchmann, K., & Briner, R. B. (1998). Evidence of mood linkage in work groups. *Journal of Personality and Social Psychology*, 74(6), 1504–1515.
90. Trogdon, J., Nonnemaker, J., & Pais, J. (2008). Peer effects in adolescent overweight. *Journal of Health Economics*, 27(5), 1388–1399.
91. Tumen, S. and Zeydanli, T. (2015). Is happiness contagious? Separating spillover externalities from the group-level social context. *Journal of Happiness Studies*, 16(3), 719–744.
92. Van Workum, N., Scholte, R. H. J., Cillessen, A. H. N., Lodder, G. M. A., & Giletta, M. (2013). Selection, deselection, and socialization processes of happiness in adolescent friendship networks. *Journal of Research in Adolescence*, 23, 563–573.
93. Verma, S., & R. Larson (1999). Are Adolescents more emotional? A study of the daily emotions of middle class Indian adolescents. *Psychology and Developing Societies*, 11(2), 179–194.
94. Visser, V.A., van Knippenberg, D., van Kleef, G.A., and Wisse, B. (2013). How leader displays of happiness and sadness influence follower performance: Emotional contagion and creative versus analytical performance. *The Leadership Quarterly*, 24(1), 172–188.
95. World Health Organization (2001). *The world health report 2001 - Mental health: new understanding, new hope*. World Health Organization.
96. World Health Organization (2003). *Caring for children and adolescents with mental disorders: setting WHO directions*. World Health Organization.
97. World Health Organization. (2017). *Depression and other common mental disorders: global health estimates* (No. WHO/MSD/MER/2017.2). World Health Organization.

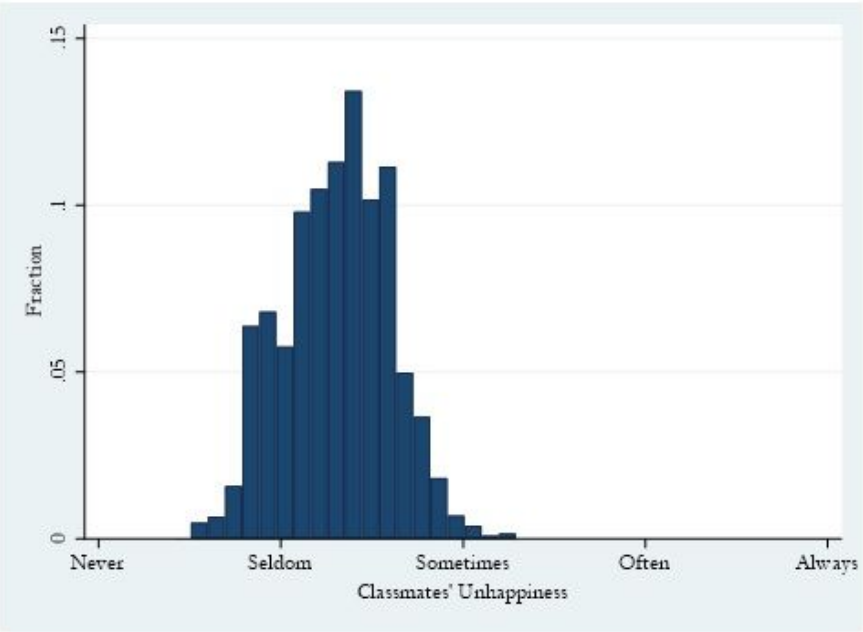
98. Xu, D., Zhang, Q., & Zhou, X. (2020). The impact of low-ability peers on cognitive and non-cognitive outcomes: random assignment evidence on the effects and operating channels. *Journal of Human Resources*.
99. Zhang, A. (2019). Peer effects on mental health: Evidence from random assignment into classrooms. Available at SSRN: https://ssrn.com/abstract=3685374
100. Zhao, L., & Zhao, Z. (2021). Disruptive peers in the classroom and students' academic outcomes: Evidence and mechanisms. *Labour Economics*, *68*, 101954.

Figures

a. Own Unhappiness



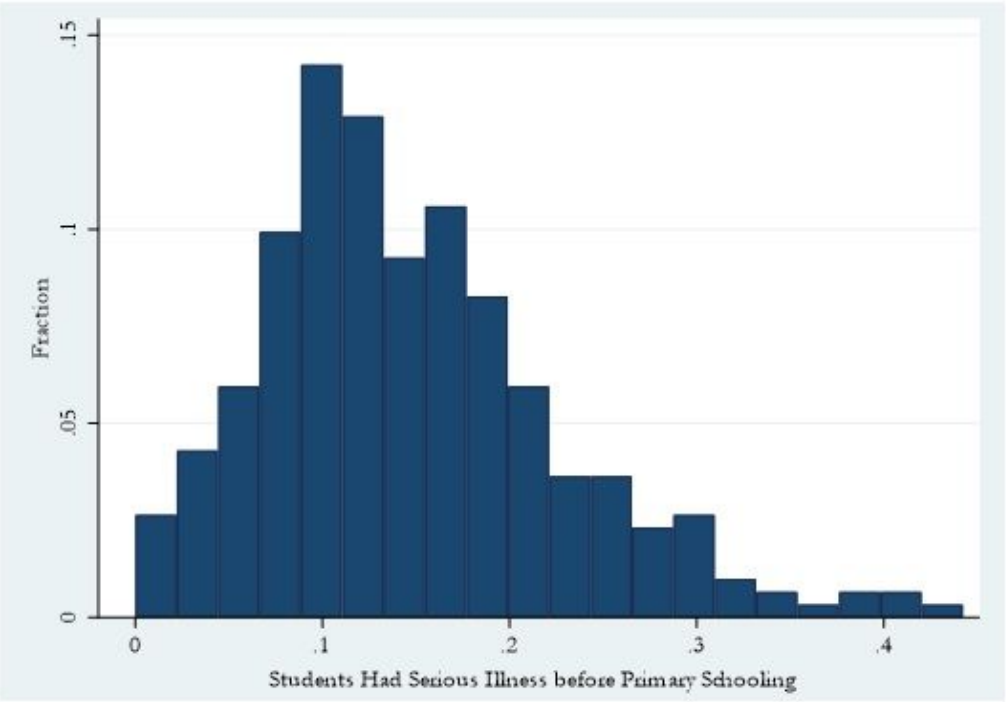
b. Classmates' Unhappiness



Notes: CEPS 2013 sample is used. Sample size is 12,677.

Figure 1

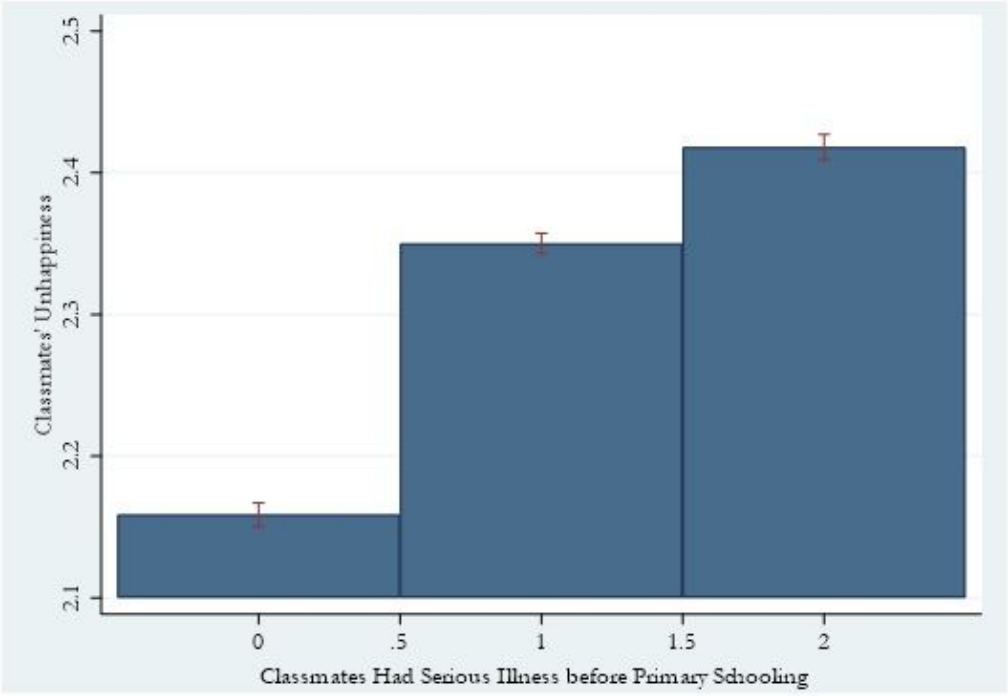
Distribution of Unhappiness on a 5-point Scale



Notes: CEPS 2013 sample is used. The unit of observation is a class. Sample size: 301.

Figure 2

Proportion of Students Had Serious Illness per Classroom



Notes: CEPS 2013 sample is used. Mean and 95% confidence intervals are presented. Sample is equally divided into three groups, Low, Medium and High, based on the value of proportion of classmates had serious illness before primary schooling. Sample size is 12,677.

Figure 3

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ZhouWangSupplementary2021NHBfinal.pdf