Peers, parents, and teachers: The role of others in student perceptions of worth and efficacy

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2021-03-21 20:47:30

Contents

Note: All code, data, figures, cited papers, and pre-planned analyses are publicly available at https://github.com/psych252/final-project-hannah-marshall.

1 Introduction

The social isolation of the COVID-19 pandemic–and the resultant deficit in physical and emotional connection between people–has recently brought to light another pandemic: mental illness. Mental illness is pervasive and destructive. It requires global attention and responsive intervention. One in five U.S. adults live with a mental illness (Lipari and Park-Lee 2019). Children are comparably affected: Nearly one in ten children ages five to 16 have a clinically diagnosable mental health problem (Green et al. 2005). Adolescents are disproportionately affected: Almost half of adolescents ages 13 to 18 have had a mental disorder (Merikangas et al. 2010). Considering the paucity of information on unique manifestations of mental illness in children and adolescents, these are likely conservative estimates.

There is a major deficiency in how society tends to address this ubiquity of mental illness: We fixate on the effects–usually in adulthood–and largely disregard opportunities for preventative work. Fifty percent of mental health problems are established by age 14 and 75% are established by age 24 (Kessler et al. 2005). If we intervene early–during childhood and adolescence–we may be able to curb mental health issues long before they arise.

Some countries around the world have begun doing this by instituting mental health education into schools. New York Bill A3887B, signed into law in 2016, requires mental health education to be a part of health education across all grade levels (State of New York 2015). New York is among at least nine states that legally require some form of mental health curriculum (Lubell and Snow 2019).

While explicit mental health education is necessary to prevent and prepare children to deal with academic, emotional, and psychological stressors, we can also attack mental illness from a different angle: by tailoring existing structures to promote mental wellness. This might involve providing additional training of and support for teachers, building social support programs which enable parents to take more active parts in their children's lives, helping children build supportive peer relationships, or creating rich opportunities for students to build self-esteem. To determine which programs would best support students' mental wellness, it is first necessary to determine which academic, familial, and social factors have the most prominent effects on student mental health.

In the current study, we pose the research question "How do peer perceptions, parent involvement, and teaching quality correlate with American students' self-concept (perception of worth) and self-efficacy (perception of control)?"

1.1 Hypotheses

Our confirmatory analyses test the following hypotheses:

- Hypothesis 1: Controlling for peer assessment, greater parent involvement in school life will predict students' more positive self-concept.
- Hypothesis 2: Controlling for grades, better teaching will predict students' greater self-efficacy.

2 Methods

2.1 Sample

The sample was drawn from a 1990s data set, in which the initial sample included 24,599 eighth-graders, one parent of each student, two teachers of each student, and each student's school principal. The study design was longitudinal: Students were first surveyed in 1988, and in 1990 "a subsample of base year participants and nonparticipants was followed and resurveyed... The [1990] sample was freshened to represent tenth-graders" (National Center for Education Statistics n.d.).

If parent involvement predicted self-concept with an effect size of .30 (our minimum effect of interest), we would be able to detect the effect with an alpha of .05 and "100% power." The same power is reached when detecting the effect of teaching quality on self-efficacy. To detect the same effect with 80% power, only 125 participants would have been required.

It can be assumed that the larger sample was surveyed in order to ensure a nationally representative sample and to correct for the decrease in power when making multiple comparisons. (The main purpose of the original study was to conduct exploratory analyses on the students' reported experiences.) Because the sample is so large, nearly every effect will be statistically significant. Thus, we can only use our analyses to estimate effect sizes and directionality of effects, but we cannot conduct truly meaningful null hypothesis significance testing.

2.2 Data Collection and Coding

The students were surveyed on school, work, home, and neighborhood environment; educational resources and support; interpersonal relationships; and educational and occupational aspirations. Questions and response codes can be found at https://hci.stanford.edu/courses/cs448b/data/nels/NELS_data_codebook.pdf.

Some of the original survey response options do not meet contemporary standards of ideal measurement. For instance, some answers to survey items were coded as 1 = *not at all*, 2 = *once or twice*, and 3 = *3 or more times*: The qualitative difference between *not at all* and *once or twice* does not equate to the quantitative difference between 1 and 2. Similarly, the difference between 1 and 2 does not equate to the difference between 2 and 3. Where possible, we amended issues like this by re-coding survey items. We re-coded other variables for understandability. Questions used in our analyses and how they were re-coded can be found at https://github.com/psych252/final-project-hannah-marshall/blob/master/code/Variables.md.

2.3 Variables

Because this suvery data was not collected in a controlled experiment, no variables were manipulated. Thus, relationships between "independent" and "dependent" variables cannot be assumed to be causal.

When testing Hypothesis 1, we treated parent involvement as the independent variable and self-concept as the dependent variable. We treated peer assessment as an additional fixed effect, which we controlled for, and subject as a random intercept. Parent involvement was a composite measure of eight related survey items. Self-concept was a composite measure of seven related survey items. A single survey item was used as our peer assessment variable.

When testing Hypothesis 2, we treated teaching quality as the independent variable and self-efficacy as the dependent variable. We treated grades as an additional fixed effect, which we controlled for, and subject as a random intercept. Teaching quality was a composite measure of five related survey items. Self-efficacy was a composite measure of six related survey items. Grades were a composite measure of each student's self-reported English, Mathematics, Science, and Social Studies grades.

Self-concept, teaching quality, and self-efficacy composite measures were calculated by reversing reverse-scoring items, z-scoring each response, and averaging nonmissing z-scores. Parent involvement survey items were dummy coded and non-missing responses were averaged. Non-missing grades were averaged across subject areas.

2.4 Analyses

2.4.1 Primary Analyses

To test Hypothesis 1, we used a linear mixed effects model with parent involvement and peer assessment as fixed effects and subject as a random intercept: s_concept ~ p_involvement + important_peer + (1 | student_id).

To test Hypothesis 2, we used a linear mixed effects model with teaching quality and grades as fixed effects and subject as a random intercept: control ~ teaching_quality + grades + (1 | student_id).

When modeling, we used ANOVAs to compare nested compact models with augmented models. Wherever appropriate, we used an alpha of .05 as the standard criterion for indicating statistical significance. We checked our model assumptions (that errors have constant variance and are normally distributed) with two visualizations: one plot with model predictions on the x-axis and residuals on the y-axis, and a density plot of the residuals.

We excluded all missing data from our analyses. Where a measure was not performed on any participants during the follow-up (1990) survey, we used values from the initial (1988) survey.

2.4.2 Exploratory Analyses

To support our analysis of Hypothesis 2, we assessed the mediation effect of academic achievement between teaching quality and self-efficacy by calculating its average causal mediation effect (ACME).

3 Results

3.1 Confirmatory Analyses

3.1.1 Hypothesis 1

We detected a slight effect of parent involvement on self-concept, where students whose parents are more involved in their school life have a healthier self-concept (Figure 1). We see that this effect is strongest when students perceive themselves as being not at all important to their peers (Figure 2).

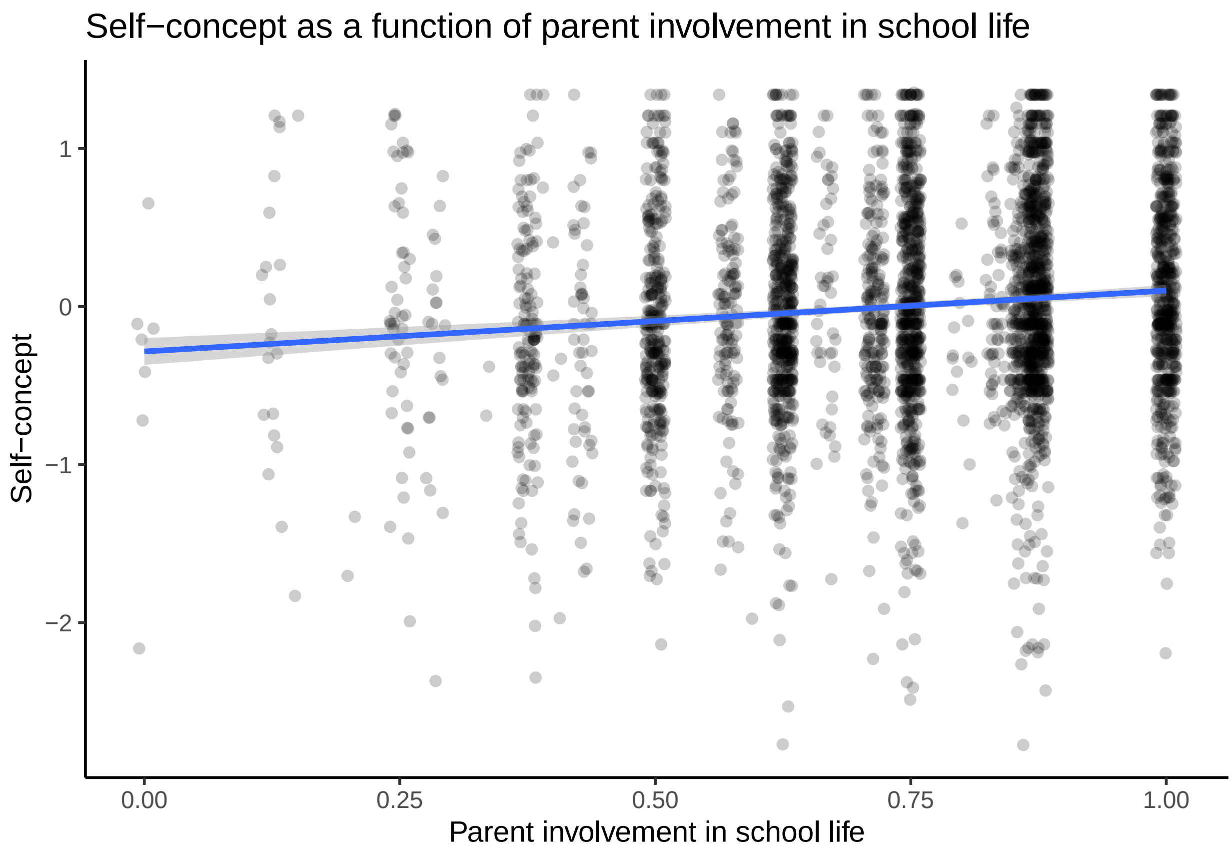

Figure 1: Each point represents an individual observation at a given timepoint. Points have been jittered slightly (by .01) for readability. Blue line represents a simple linear regression (method = lm). Ribbons represent pointwise 95% confidence intervals on the linear model.

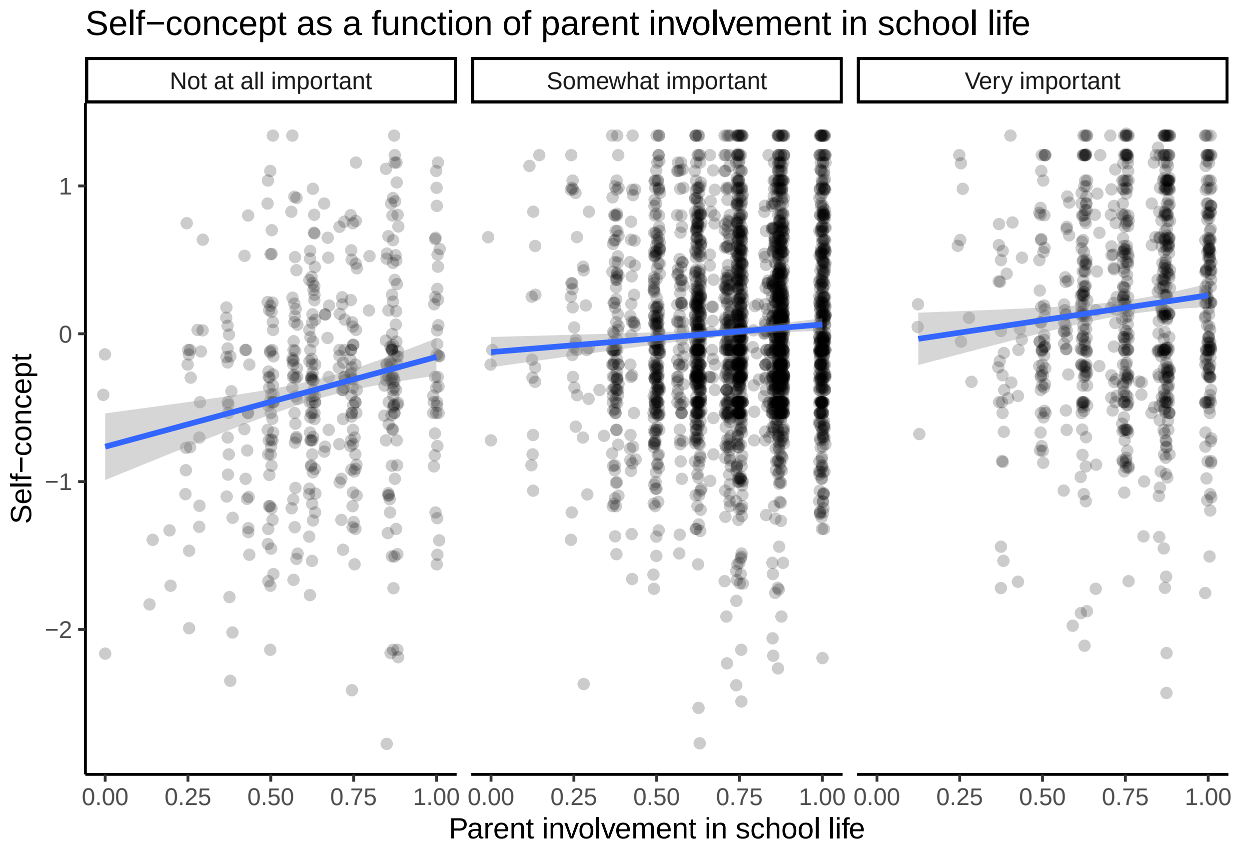

Figure 2: Each point represents an individual observation at a given timepoint. Points have been jittered slightly (by .01) for readability. Blue lines represent simple linear regressions (method = lm). Ribbons represent pointwise 95% confidence intervals on the linear models. Data are faceted by student responses to the question "How do you think other students in your classes see you?"

Fitting the data to a linear mixed effect model (s_concept ~ p_involvement + important_peer + (1 | student_id)) revealed that when peer assessment is held constant, every unit increase in the composite of parent involvement increases the composite of self-concept by .30, $t(1922) = 4.45$. When parent involvement is held constant, every unit increase in self-reported peer assessment increases self-concept by .24, $t(1903) = 10.52$.

By conducting an ANOVA between our model and a model that excludes peer assessment (s_concept ~ p_involvement + (1 | student_id)), we confirmed that a model that takes both parent involvement and peer assessment into account predicts self-concept significantly better, $X^2 = 107.68$, $p < .001$, which was foreseeable considering our large sample.

To more meaningfully quantify the difference between the two models, we compared their marginal R^2 values, which represent the variance explained by the fixed effects in the model. Based on this analysis, the fixed effects of the model which includes peer assessment explains an addition 4.09% of the variation in self-concept, $R^2_{compact} = .0128$, $R^2_{augmented} = .0537$.

We confirmed that our model was generally representative of the true data by simulating new data and visualizing it against the true data (Figure 3, Figure 4). However, the self-concept composite measure had an upper bound of ~ 1.35, which is exceeded by the simulation.

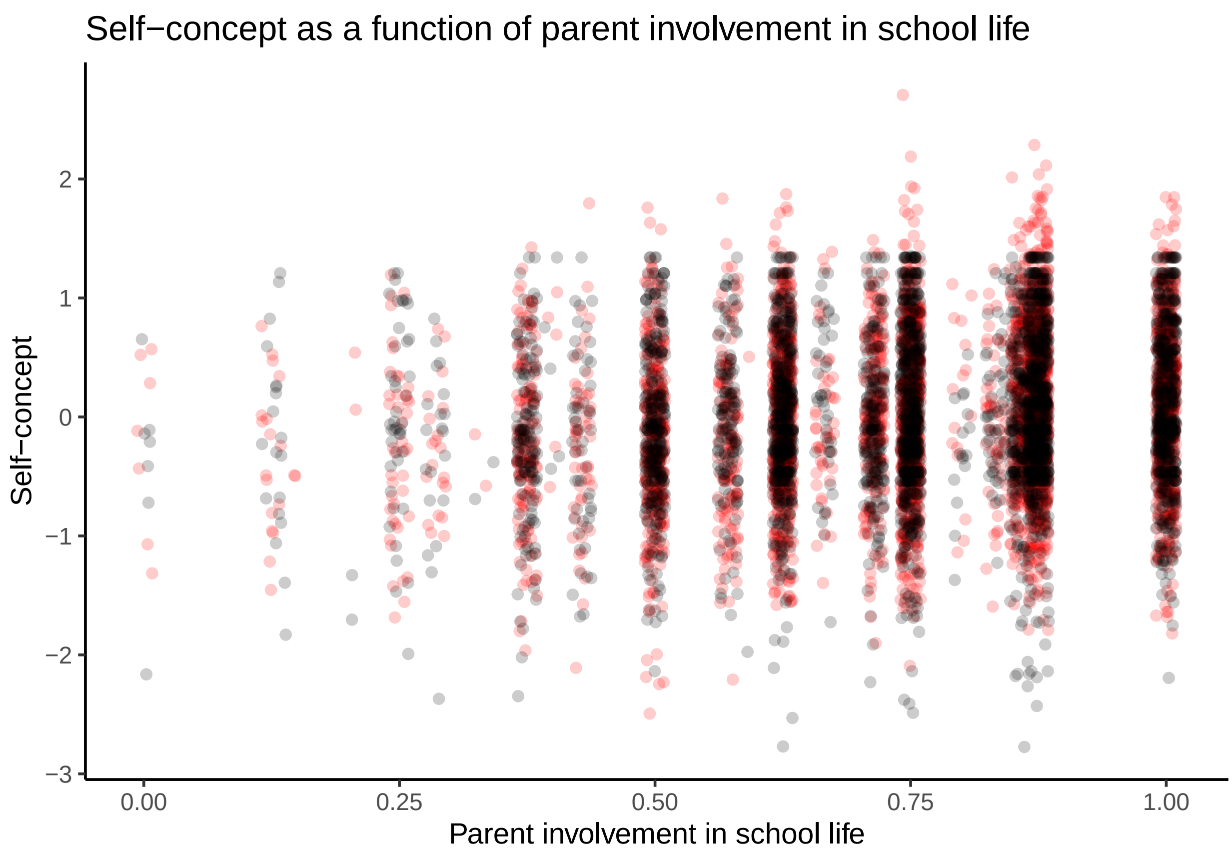

Figure 3: Each point represents an individual observation at a given timepoint. Black points represent true data. Red points represent simulated data. Points have been jittered slightly (by .01) for readability.

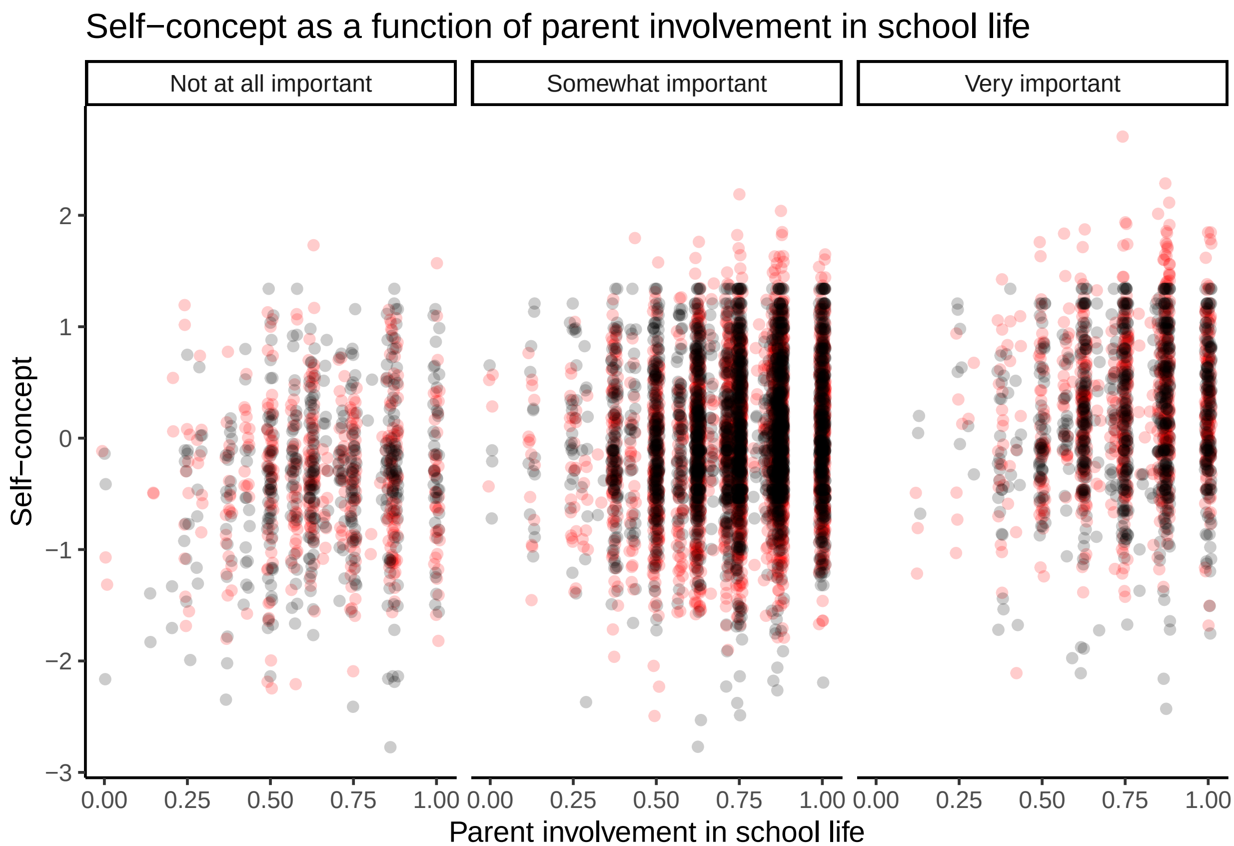

Figure 4: Each point represents an individual observation at a given timepoint. Black points represent true data. Red points represent simulated data. Points have been jittered slightly (by .01) for readability. Data are faceted by student responses to the question "How do you think other students in your classes see you?"

3.1.2 Hypothesis 2

We detected a prominent effect of teaching quality on self-efficacy, where students who perceive the teaching quality at their school as better feel more self-efficacious. (Figure 5). However, we did not see a pronounced variation in effect after faceting the data by grades (Figure 6).

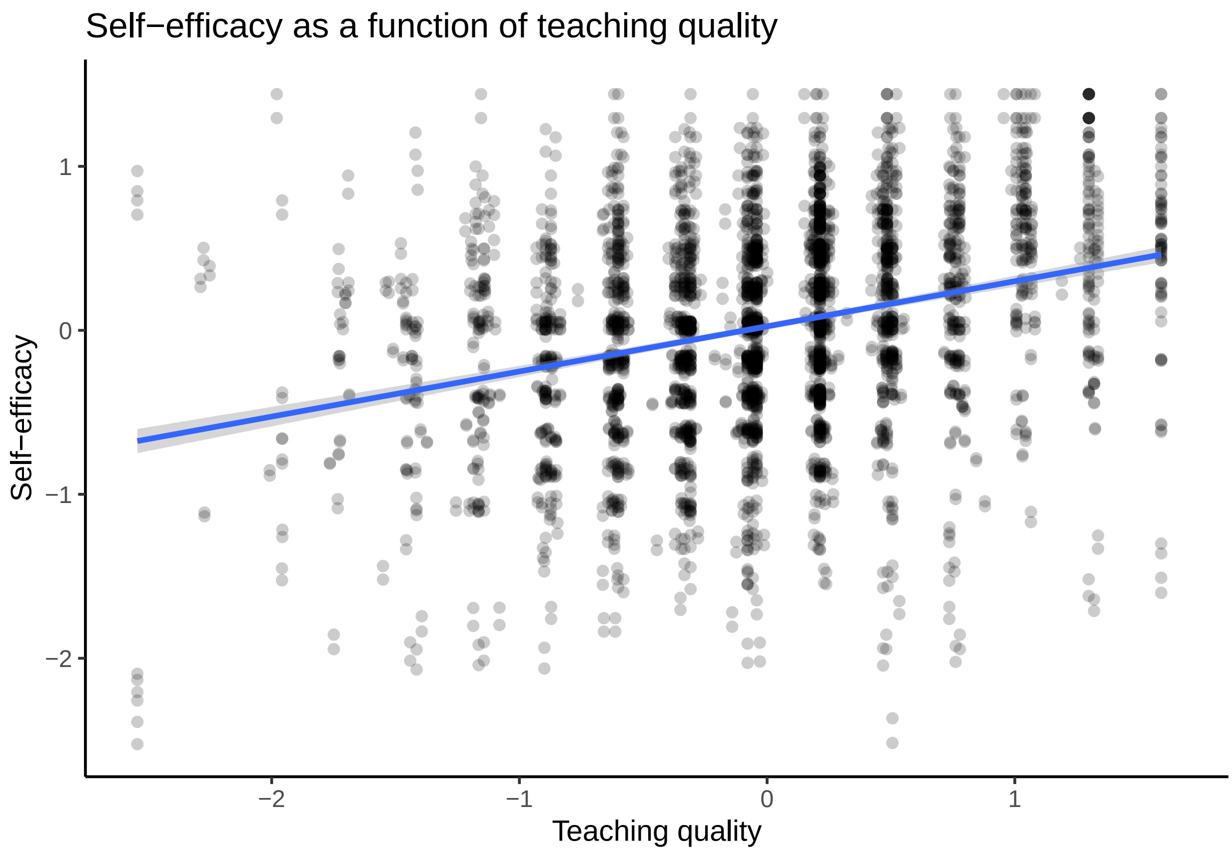

Figure 5: Each point represents an individual observation at a given timepoint. Blue line represents a simple linear regression (method = lm). Ribbons represent pointwise 95% confidence intervals on the linear model.

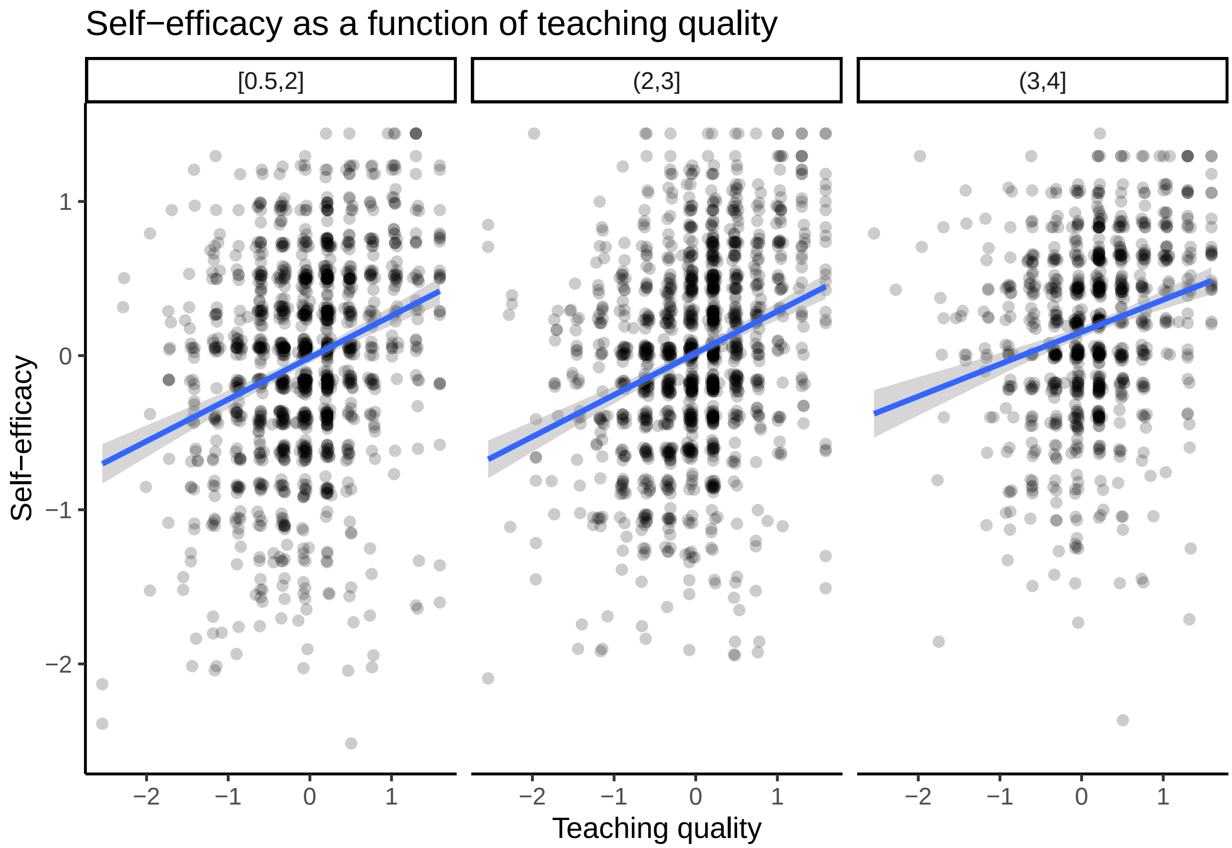

Figure 6: Each point represents an individual observation at a given timepoint. Blue lines represent simple linear regressions (method = lm). Ribbons represent pointwise 95% confidence intervals on the linear models. Data are faceted by terciles of the composite measure of student grades, where 4 = mostly As, 3 = mostly Bs, 2 = mostly Cs, 1 = mostly Ds, and .5 = mostly less than Ds.

Fitting the data to a linear mixed effect model (control ~ teaching_quality + grades + (1 | student_id)) revealed that when grades are held constant, every unit increase in the composite of teaching quality increases the composite of self-efficacy by .27, $t(1948) = 13.54$. When teaching quality is held constant, every unit increase in self-reported grades decreases self-efficacy by .03, $t(1675) = -29.81$.

By conducting an ANOVA between our model and a model that excludes grades (control ~ teaching_quality + (1 | student_id)), we confirmed that a model that takes both teaching quality and grades into account predicts self-efficacy significantly better, $X^2 = 705$, $p < .001$, which was foreseeable considering our large sample.

When comparing the models' marginal R^2 values, we found that the fixed effects in the model which includes grades only explains an additional .07% of the variation in self-efficacy, $R^2_{compact} = .0820$, $R^2_{augmented} = .0827$.

We confirmed that our model was generally representative of the true data by simulating new data and visualizing it against the true data (Figure 7, Figure 8). However, the self-efficacy composite measure had an upper bound of ~ 1.44, which is exceeded by the simulation.

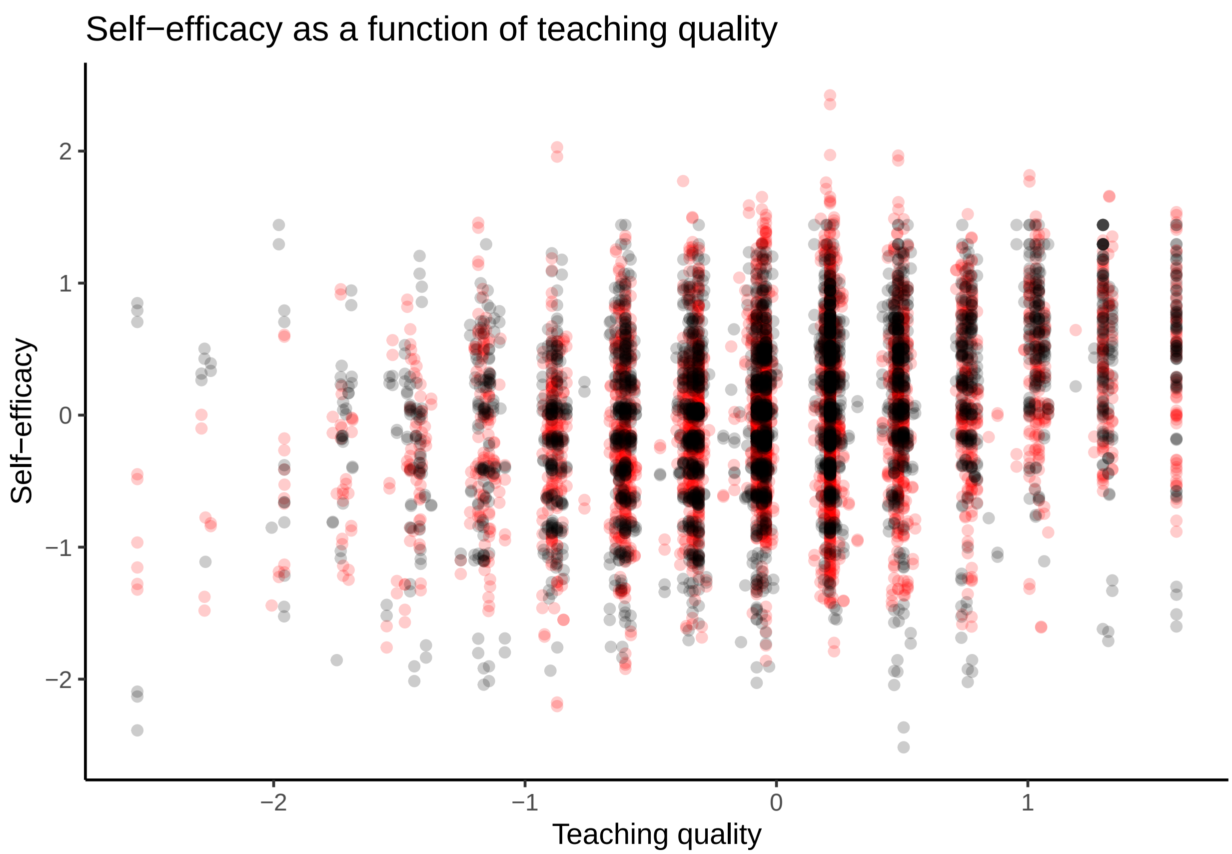

Figure 7: Each point represents an individual observation at a given timepoint. Black points represent true data. Red points represent simulated data.

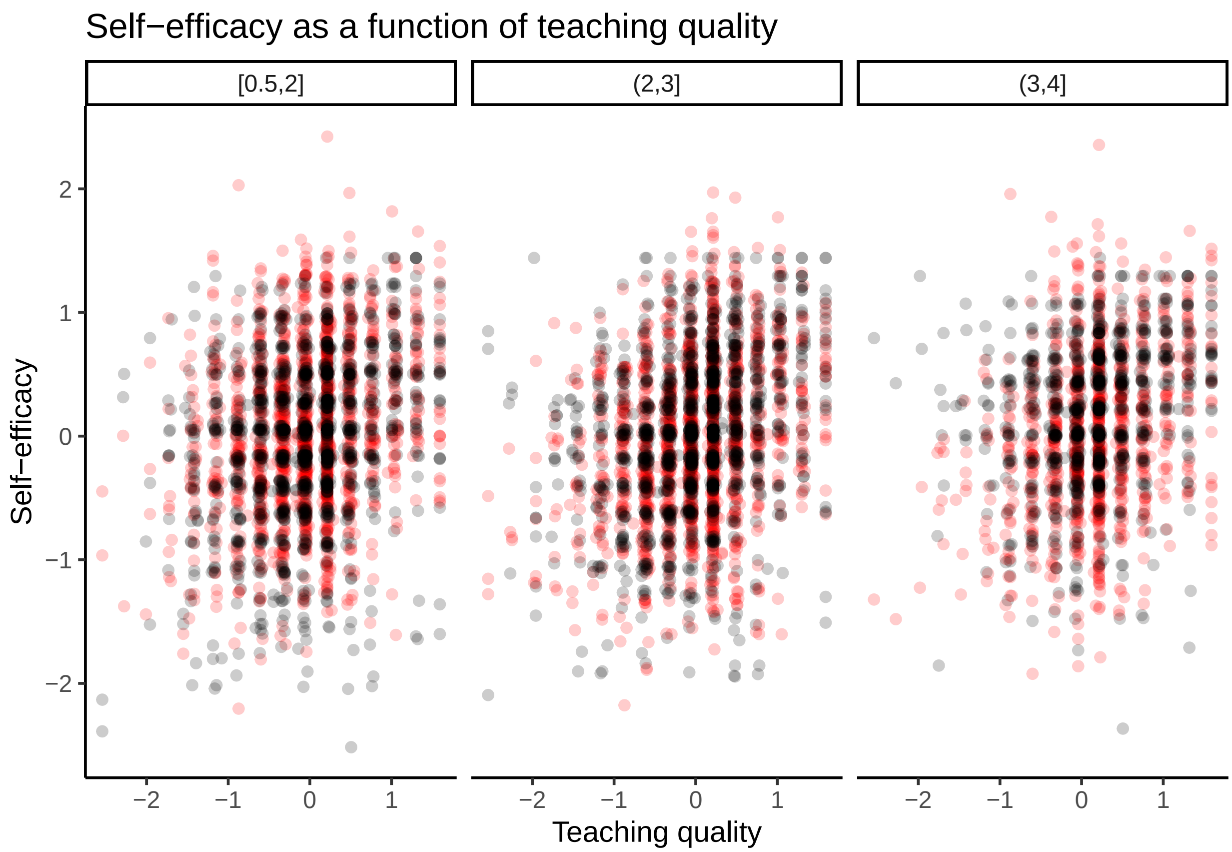

Figure 8: Each point represents an individual observation at a given timepoint. Black points represent true data. Red points represent simulated data. Data are faceted by terciles of the composite measure of student grades, where 4 = mostly As, 3 = mostly Bs, 2 = mostly Cs, 1 = mostly Ds, and .5 = mostly less than Ds.

3.2 Exploratory Analyses

Mediation Analysis

To support our analysis of Hypothesis 2, we assessed the mediation effect of academic achievement between teaching quality and self-efficacy. Our mediation analysis revealed no notable mediation of academic achievement between teaching quality and self-efficacy, $ACME = .01$. Because the sample was so large, all of the relevant effects were statistically significant (Figure 9). However, we saw no change in the magnitude of the estimate regarding the relationship between teaching quality and self-efficacy once grades were taken into account. The linear mixed effects model that used only teaching quality as a fixed effect predicted that for every unit increase in teaching quality, self-efficacy would increase by .27. The linear mixed effects model that used both teaching quality and grades as fixed effects predicted that when grades are held constant, every unit increase in teaching quality would increase self-efficacy by .27 and change.

Table 1: Output from mediation analysis assessing mediation of academic achievement between teaching quality and self-efficacy. All p-values indicate statistical significance due to the large sample size.

	Estimate	95% CI Lower	95% CI Upper	p-value
ACME	0.0106086	0.0069888	0.0150718	0
ADE	0.2570781	0.2173098	0.2915943	0
Total Effect	0.2676867	0.2283735	0.3018065	0
Prop. Mediated	0.0396307	0.0257619	0.0601130	0

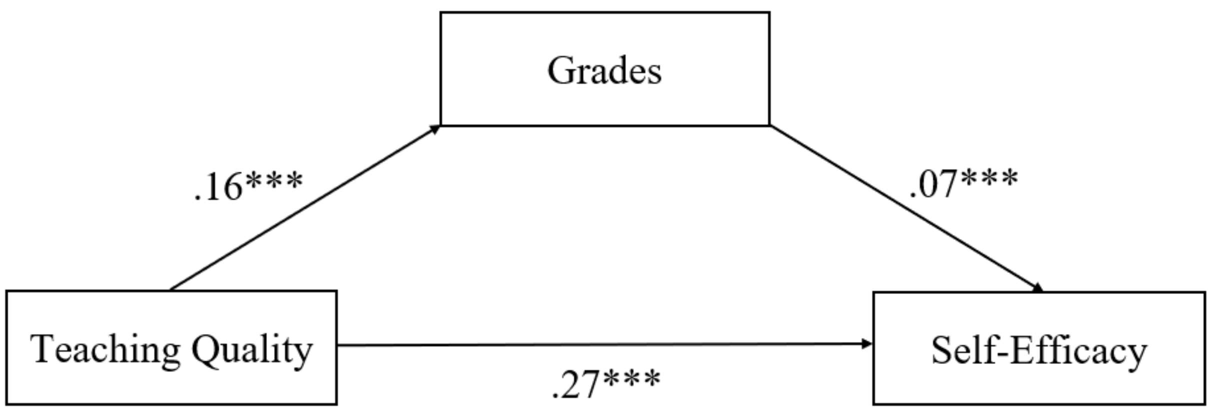

Figure 9: Mediation diagram illustrating mediation of academic achievement between teaching quality and self-efficacy.

4 Discussion

Our study provides evidential support for both of our hypotheses. Controlling for peer assessment, greater parent involvement in academic activities predicts students' more positive self-concept. Controlling for grades, better teaching predicts students' greater self-efficacy; however, our analyses showed that controlling for grades is unnecessary.

We found that students whose parents are more involved in their school life have a healthier self-concept. This may be because when parents take a vested interest in their children's success, children think of their abilities as worth investing in. Although, the causation may be more complex. For example, parents who are more involved in their children's schooling may also tend to build their children's confidence in other ways, which may lead to healthier self-concept. Alternatively, parents who have time and can afford to be more involved in their children's school life are likely to be of higher SES, which may have latent effects on their children's self-concept.

We also found that students who perceive themselves as more important to their peers have a healthier self-concept. It is intuitive that a heightened sense of social value and importance and belonging among peers would correlate with greater self-worth.

Finally, students who perceive the teaching quality at their schools as better feel more self-efficacious. Good teachers are able to empower students with skills which instill confidence. Teachers who recognize hard work and expressly care about their students also inspire students to believe in their own potential.

While our findings are promising, it is worthwhile to note that because these data were collected decades ago, our conclusions may not hold true among current students.

In all, our results indicate that peer perceptions, parent involvement, and teaching quality may play roles in determining American students' self-concept (perception of worth) and self-efficacy (perception of control). Thus, it may be possible to bolster students' mental wellness by creating opportunities for parents to become more involved in their children's school life, by helping students build supportive peer relationships, and by providing additional training to and support for teachers.

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