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Social Emotional Learning, Student Attendance, and Chronic Absenteeism in Pre- and Post-Pandemic Periods

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Author Note

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Abstract

We develop and implement a quasi-experimental panel data model to address the relationships between social emotional learning competencies (SEL) and annual student attendance in the pre- and post-pandemic periods. Although panel data models tend to focus on changes over time in outcomes and predictors, we develop a model that decomposes the effects of SEL into stable and transitory components. The model addresses two types of error in SEL variables: standard error due to unreliability in the measured variables and error in student average SEL as a measure of the stable component of SEL. We find that the stable measures of self-efficacy and self-management are strong positive predictors of student attendance. We construct a composite SEL measure that optimally combines four SEL measures. Effect size estimates of the stable SEL composite increase from 0.138 to 0.223 between the pre- and post-pandemic periods. Effect size estimates are even higher for students with predicted attendance level at the 10% quantile level: 0.227 and 0.405 in the two periods, respectively. Although the effect sizes of SEL in both the pre- and post-pandemic periods are relatively large they explain only 5 to 10 percent of the decline in attendance. Our results establish the predictive validity of SEL measures with respect to student attendance. The estimated effects are strong enough to suggest that the causal effects of SEL may be large, especially for students with low expected attendance.

Social Emotional Learning, Student Attendance, and Chronic Absenteeism in Pre- and Post-Pandemic Periods

In this paper we develop and implement a quasi-experimental panel data model to address the relationships between social emotional learning competencies (SEL) and annual student attendance and the changes in those relationships between pre- and post-pandemic periods. Although panel data models tend to focus on changes over time in outcomes and predictors, we develop a model that decomposes the effects of SEL into stable and transitory components. We consider predictive analytics applications of the model in early warnings systems and model design and assumptions that justify interpretation of parameter estimates as causal. The models are estimated using pre-pandemic data covering school years 2015-16 to 2017-18 (three years of panel data) and post-pandemic data covering school years 2021-22 to 2023-24 (three years of panel data). The models focus on student outcomes in grades four to eight.

Our research is timely since the rate of chronic absenteeism has skyrocketed in the years after the COVID pandemic. Based on data from 40 states and District of Columbia, Dee (2023) shows the state average chronic-absenteeism (defined as a student missing 10% or more school days) rate has jumped from 14.8 percent in 2018-2019 to 28.3 percent in 2021-2022, a 91-percent increase. This overall increase in chronic absenteeism masks substantial inequality across schools and students. For instance, in California, the number of schools with extremely high rates (30% or more) of chronic absenteeism has increased three times compared to pre-pandemic levels. The incidence of chronic absenteeism increased among foster youth, native Americans, African American students, and students with disabilities (Chang et al, 2024). The biggest hurdle in implementing many school-based interventions appears to be the lack of engagement from those students who fall behind (Carbonari et al, 2024; Callen et al, 2022; Barry and Sass 2022; Robinson 2022).

This paper is motivated by the literature on risk factors that contribute to chronic absenteeism and social-emotional learning studies. We discuss the implications of this literature later in the paper after we define the four SEL constructs measured in our data.

There is burgeoning empirical research focusing on examining the impact of SEL on attendance and achievement. Kanopka et al (2024) found that changes in self-reported SEL measures predict changes in attendance and achievement by leveraging longitudinal CORE district data from 2015-2017 and using a student fixed effect model. Snyder et al (2010) used a randomized controlled trial to examine a school based SEL program on achievement and absenteeism, in which they found that intervention schools have lower absenteeism compared to control group. As in the paper by Kanopka et al (2024), our paper investigates the effects of reported measures of SEL on student outcomes. We do not provide evidence on why student reports of SEL change over time or the effects of programs designed to affect SEL. The paper provides insights on how SEL measures can be used to evaluate the effects of SEL interventions.

Summary of Results

In this section we present an extensive summary of our models, methods, and results. Our research contributes new findings on the relationship between measures of social emotional learning (SEL) and student attendance and chronic absenteeism and develops new statistical/econometric models of student attendance and chronic absenteeism. We explore this relationship using a large longitudinal data set that includes data on student attendance and student survey-reported measures of four SEL constructs: self-efficacy, self-management, growth mindset, and social awareness.

Our model of student attendance embeds three important features. First, we separate the effects of predictors (SEL constructs in our application) into stable/student average and transitory effects. Most policy and evaluation studies focus entirely on the latter. We present a hypothetical SEL factor model that demonstrates that the causal effects of predictors need not be confined to changes in the predictors, the focus of standard fixed effects evaluation models. Second, we adopt a model that is intended to capture the true data generating process (DGP) between student attendance and predictors. In this model, similar in design to a probit model, the effects of predictors are nonlinear: the effects are weaker for students with high expected attendance and stronger for students with low expected attendance. We formalize the view that the effects of chronic absenteeism are especially harmful to students by evaluating the effects of SEL on these students. Third, we extend the model to account for two types of error in SEL variables: standard error due to unreliability in the measured variables and error in student average SEL as a measure of the stable component of SEL.

We report estimates of model parameters and effect size estimates to allow for meaningful comparisons between the different effects. Note that we treat the effects reported in this paper as upper bound estimates of the causal effect of SEL on student attendance given the possibility that these variables are correlated with causes of attendance not included in the model and the estimates are based on a quasi-experimental model. Nonetheless, the estimated effects are strong and are important from the policy, evaluation, and measurement perspectives, as discussed below.

Drawing from the psychology literature on risk factors that contribute to chronic absenteeism, we hypothesize that risk factors and SEL constructs such as self-efficacy and self-management measure the same personality traits or characteristics associated with determinants of chronic absenteeism. We find support for this hypothesis: the effects of student average or stable measures of self-efficacy and self-management are strong positive predictors of student attendance and chronic absenteeism. In contrast, the estimated coefficients on growth mindset and social awareness are negative and statistically significant but relatively small. Since we do not think that growth mindset and social awareness have genuine negative effects on student attendance, we conjecture that the negative coefficients arise because self-efficacy and self-management, as measured given the survey questions listed in Appendix A, measure aspects of growth mindset and social awareness, as well as the true self-efficacy and self-management constructs. We present the results of a hypothetical SEL factor model that shows that these negative results may be an artifact of the structure of the SEL survey (especially in the post-pandemic period). We construct a composite SEL measure that optimally combines the four SEL measures. Given that the coefficients on self-efficacy and self-management variables are collectively larger than the effects of growth mindset and social awareness, we view the composite SEL variable as a measure that largely represents self-efficacy and self-management. Our results are also consistent with the view that a general SEL factor is the essential predictor of student attendance. Bolt, Wang, and Meyer (2025), in their multi-level bifactor model of SEL provide support for the existence of a strong general SEL factor.

The effects of all SEL measures channel primarily through the stable and student average measures of these variables, rather than through transitory changes in these variables. These effects are stronger in the post-pandemic period than in the pre-pandemic period. Indeed, the effects of self-efficacy and composite SEL more than double in the post-pandemic period. Effect size estimates of the stable SEL composite measure increase from 0.1378 to 0.2225 between the pre- and post-pandemic periods. These effects apply to the average student and are very large, but, as expected, effect size estimates are even higher for students with predicted attendance level at the 10% quantile level, especially in the post-pandemic period. Effect sizes equal 0.227 and 0.405 in the pre- and post-pandemic periods, respectively. These results confirm the widely reported fact that chronic absenteeism has been especially high in the post-pandemic period and demonstrate that differences across students and over time are highly correlated with differences in the stable and student average components of self-efficacy, self-management, and the SEL composite.

Although the effect sizes of SEL in both the pre- and post-pandemic periods are relatively large, especially for students with low predicted attendance, they explain only a small percentage of the decline over time in student attendance. Although we caution against interpreting the results from our quasi-experimental model of student attendance as fully causal, the fact that changes in SEL over time could account for 5 to 10 percent of the decline in attendance is plausible. Moreover, our results establish the predictive validity of SEL measures with respect to student attendance, although that predictive power resides primarily in the student average or stable measures of SEL.

The results in this paper are important from policy, evaluation, and measurement perspectives. First, the research confirms that the SEL survey administered to students in our sample measure constructs that are highly valid in terms of predictive validity, although predictive power resides primarily in the stable and student average measures of these constructs. Second, student data on average values of self-efficacy and self-management are well-suited for use in predictive analytics and early warning systems that identify students at risk of future adverse student outcomes (student attendance in this study). Third, although it is appropriate to treat the estimated effects as upper bound estimates, the effects are strong enough to suggest that the causal effects of SEL may be large, especially for students with low expected attendance. The methods considered in this paper are consistent with a policy focus on chronic absenteeism but do so using models that represent the entire spectrum of student attendance. Fourth, the results of this paper suggest that it may be sensible to implement and rigorously evaluate interventions to increase student self-efficacy and self-management, particularly for students with low expected attendance. However, evaluations of the effectiveness of SEL should arguably focus on the effects of interventions on stable (student average) SEL outcomes rather than year-to-year changes. Finally, given the strong results obtained using the data, time periods, and models used in this study, further quasi-experimental research should be conducted to assess the robustness of the results.

Methodological Innovations. The statistical/econometric contributions of the project are potentially important and applicable to other research applications using panel data. We consider two dimensions of the student attendance model: the left hand (outcome) side and the right hand (predictor) side. With respect to the outcome side, we implement an approach to measuring student attendance that allows the effects of predictors to be nonlinear. This approach is important in that it aligns with the public policy concern with chronic absenteeism and facilitates evaluation of the equity effects of predictors and interventions. With respect to the predictor side, we consider alternative panel data models that provide very different information on the effects of predictors.

Student attendance as an outcome variable. Our measure of student attendance addresses the fact that the distribution of annual student attendance rates is highly left-skewed. This distribution is an expected result since the attendance rate is a proportion based on the average of binary daily attendance outcomes. As in a binary probit model we assume that the relationship between raw attendance rates and predictors is best represented by the normal cumulative distribution function (or probit function). We accordingly transform the attendance rate using the inverse probit function. One of the major advantages of this approach is that the model fits within the class of generalized linear models (GLM) and thus the right hand-side of the model is a linear regression with random student effects.

We develop an approach to measuring the effect sizes that is transparent and easy to implement. Indeed, all effect size estimates can be generated from the results of single models based on pre-pandemic and post-pandemic data, respectively.

Development of the predictive (right hand) side of the model. We begin model development of the right-hand side of the model using a standard evaluation method, the fixed effects (FE) (within variance) model. A limitation of this approach is that it yields estimates of predictors solely based on changes (or transitory within variation) in predictors. The fixed effects are treated as nuisance parameters that must be included but provide no useful insight into the determinants of the outcome of interest (student attendance). We instead adopt the correlated random effects (CRE) model (Mundlak, 1978; Wooldridge, 2010) which yields estimates of within-variance parameters that are identical to those of the FE model but also provides estimates of the effects of student average variables. In both cases, however, it is customary to assume that the parameters of interest are the coefficients based on changes in predictors.

Expand the focus. We consider a hypothetical factor analysis model of the SEL constructs that demonstrates that the coefficients on the student average variables potentially contain valid information on the causal effects of predictors. We thus adopt the CRE model as our maintained model and report estimates of the effects of both the transitory and student average (stable) predictors. We treat the effects estimates reported in this study as upper bound estimates of the causal effect of SEL on student attendance given the possibility that these variables are correlated with causes of attendance not included in the model and the estimates are based on a quasi-experimental model. The value of this expanded approach is that we can report estimates of both the effects of transitory and stable (student average) components unlike traditional approaches which report only the former. Our model estimates indicate that the effects of the stable and student average components dwarf the estimates of the transitory component.

Correction bias due to measurement error. Finally, we develop a model that accounts for two types of error in SEL variables: error due to unreliability in the measured variables (statistical error) and error in student average SEL as a measure of the stable component of SEL (conceptual error). We show that correcting for both types of measurement error yields increased estimates of the effects of the transitory and stable SEL components, and the estimates are robust to alternative assumptions about the structure of measurement error. Perhaps surprisingly, correction for statistical error primarily affects estimates of the effects of transitory SEL whereas correction for conceptual error solely affects estimates of the effects of the stable SEL component. This stems from the fact that it is not possible to distinguish between statistical and conceptual error since only the sum of the two components is known. Imposing the externally provided variance of statistical error automatically determines the value of conceptual error.

Data and Variables

The data used in this study come from about thirty school districts in California that are members of a consortium of large urban school systems known as the CORE Districts data collaborative. CORE districts have been administering a common set of surveys to all students about non-academic outcome of student success in Grades 4 through 12 for several years. Our study uses panel data for students in grades 4 to 8 from pre-pandemic school years 2015-16 to 2017-18 and post-pandemic school years 2021-22 to 2023-24. The dataset includes data on annual student attendance, students' demographics such as gender, race and ethnicity, English learner status, and students with disability status.

The SEL variables are based on a student survey containing 18 questions within four constructs. As with many surveys, not all students complete all items on the SEL survey. Our research sample includes students who completed at least 50% of the items within each SEL construct.

Students rate themselves on the same questions using a 5-point Likert scale with higher scores indicating strong SEL competence (1= Never or almost never, 5= Almost all the time). Appendix A provides a complete list of the survey items used in SEL survey. The four SEL constructs are:

- **Self-management**, also referred to as self-control or self-regulation, is the ability to regulate one's emotion, thoughts, and behaviors effectively under different circumstances, such as managing stress, delaying gratification, motivating oneself, and setting and working toward personal and academic goals (Collaborative for Academic Social and Emotional Learning [CASEL], 2005).
- **Self-efficacy** is the belief in one's ability to succeed in achieving an outcome or reaching a goal. Self-efficacy reflects confidence in the ability to exert control over one's own motivation, behavior, and environment and allows students to become effective advocates for themselves (Bandura, 1997).

- **Growth mindset** is the belief that one's intelligence is not fixed, instead it can grow with effort. Students with a growth mindset believe that they can develop their skills through effort, practice, and perseverance. The growth mindset survey items administered in the pre- and post-pandemic periods differed somewhat. The items administered in the pre-pandemic period were designed to elicit rejection of a fixed mindset and thus tended to be negatively worded. Bolt et al (2020) showed that some students were confused by the wording of these items. The items administered in the post-pandemic period were converted to positively worded versions of the same items. Wang et al (2019) compare the two alternative growth mindset measures. Although the growth mindset items differed between the two periods, we included the two measures in our empirical analyses to provide complete information on the predictive power of the available set of SEL measures.
- **Social awareness** is the ability to take the perspective of and empathize with others from diverse backgrounds and cultures, to understand social and ethical norms for behavior, and to recognized family, school, and community resources and supports (CASEL, 2005).

To facilitate the analysis, students' response to the survey items were converted into a scale score within each construct by using a generalized partial credit model (GPCM) (Meyer et al, 2018; Muraki,1992).

SEL and Student Attendance: Theoretical Motivation[1]

Research on chronic absenteeism suggests that it is caused by a myriad of factors including personal health, family circumstances, and school environment (Kearney 2008a; Kearney 2008b; Gubbels et al, 2019). Based on a meta-analysis of 75 studies, Gubbels et al (2019) categorizes 12 risk domains with large effects associated with school absenteeism, among which having a negative attitude towards school and anti-social behavior/cognitions are the dominating risk factors contributing to school absenteeism. A closer examination of the examples of these two factors (Appendix A; Gubbels et al, 2019) suggests that many of these examples are reflected in the measurement of students' social-emotional learning, in particular self-efficacy and self-management. Table 1 provides a comparison between the examples of these two risk factors and the survey questions related to self-efficacy and self-management, two constructs of social-emotional learning survey items conducted by California CORE districts and used in this study.

It can be seen from the second row of Table 1 that, for instance, if a student answers most of the four questions under self-efficacy with "not at all confident" or "a little confident", it might suggest that the student is having a negative school attitude, and he would be less likely to addend schools.

In the same token, a comparison of those two columns of the 3rd row indicates that if a student answers the majority of those five questions under self-management with "almost never" or "once in a while", the student is likely to have an anti-social behavior/cognition. In particular, examples such as child is irresponsible; child shows a lot of anger or irritability; child shows rule

[1] The author thanks Sara Hu for preparing this section.

breaking behavior; child has low self-control seem to match exactly those behaviors that self-management are meant to capture such as I got my work done right away instead of waiting until the last minute, I stayed calm even when others bothered or criticized me, I remembered and followed directions. Note that self-efficacy and self-management are distinct but related (and correlated) constructs. For example, a student demonstrating a high level of self-efficacy tends to have better self-management, likewise, a student with a negative school attitude is also likely to exhibit anti-social behavior/cognitions.

Table 1. Comparison of Social-Emotional Learning Constructs and the Risk Factors of School Absenteeism

Social-Emotional Learning Survey Items	**Examples of Risk Factors of School Absenteeism (**Gubbels et al, 2019**)**
Self-Efficacy How confident are you about the following at school? 1. I can earn an A in my classes. 2. I can do well on all my tests, even when they're difficult. 3. I can master the hardest topics in my classes. 4. I can meet all the learning goals my teachers set. (Not at All Confident, A Little Confident, Somewhat Confident, Mostly Confident, Completely Confident)	**Having a negative school attitude** Child dislikes school; Child had s academic disinterest; Child does little homework; Child does not understand the purpose of schooling; Child perceives school grades as unimportant; Child had a history of dropping out; Child doesn't feel a part of the school community; Child is often late in class; Child show low levels of school engagement; Child shows low attachment to school; Child is not committed to school; Child has low educational goals; Child shows a low motivation; Child has a negative attitude towards school; Child is not sure of high school graduation.
Self-Management Please answer how often you did the following during the past 30 days. During the past 30 days… 1. I came to class prepared. 2. I remembered and followed directions. 3. I got my work done right away instead of waiting until the last minute. 4. I paid attention, even when there were distractions. 5. I stayed calm even when others bothered or criticized me. (Almost Never, Once in a While, Sometimes, Often, Almost All the Time)	**Anti-social behavior/cognitions** Child is aggressive; Child is anti-social (but not delinquent); Child has anti-social orientation; Child has attention problems; Child has behavioral problems; Child has attitudinal problems; Child shows disruptive behavior; Child is violent; Child has conduct problems; Child has disciplinary referrals at school; Child is a bully; Child is hyperactive; Child is irresponsible; Child is prone to mischief; Child shows a lot of anger or irritability; Child shows rule breaking behavior; Child has low self-control.

Conversely, if a student answer many of the self-management and self-efficacy questions affirmatively such as mostly confident or completely confident, it indicates that the student would have a positive school attitude and pro-social behavior/cognitions, as a result he would be more likely to have a better attendance record.

The above comparison suggests that the risk factors and SEL constructs such as self-management and self-efficacy appear to measure the same personality traits or characteristics. If so, using SEL to predict attendance/absenteeism is grounded in related psychological research, and access to data on SEL and attendance would allow us to test this hypothesis empirically.

Sample Characteristics

The sample sizes for each cohort in the pre- and post-pandemic periods are reported in Table 2. As indicated in the table, the pre- and post-pandemic data sets include three grade cohorts, students in grades 4, 5, and 6; grades 5, 6, and 7; and grades 6, 7, and 8 in panel data sets spanning three years. The pre-pandemic period covers the schools years 2015-16 to 2017-18 and the post-pandemic period covers the school years 2021-22 to 2023-2024. Since our panel data models require three years of longitudinal data students are included in the models only if they have complete data for all three years. The proportion of students retained in the research samples are 68.5% and 65.2%, respectively. The data sets are large, ranging from 23 to 24 thousand unique students. Since student outcomes are observed for three consecutive years, the number of observations included in the panel data models is increased by a factor of 3.

Table 2. Number of Students by Grade Cohorts: Pre- and Post-Pandemic Periods

Pre-Pandemic Period: 2015-16 to 2017-18					**Post-Pandemic Period: 2021-22 to 2023-24**		
Cohort	**Year 1**	**Years 1 to 3**	**Retain Rate**		**Year 1**	**Years 1 to 3**	**Retain Rate**
456	12863	8936	69.5%		11864	7978	67.2%
567	13141	8543	65.0%		12335	7879	63.9%
678	10195	7323	71.8%		11992	7749	64.6%
Total	36199	24802	68.5%		36191	23606	65.2%

Table 3 presents information on the composition of the data sets for each pre- and post-pandemic

Table 3. Proportion of Students by Demographic Group and Cohort

Cohort					**Race/Ethnicity**			
Grade Span	**Pandemic Period**	**Gender (F/M)**	**ELL Status**	**Students with Disabil.**	**Hispanic**	**Asian**	**Black**	**White & Other**
456	Pre	0.494	0.544	0.093	0.632	0.178	0.054	0.101
456	Post	0.490	0.417	0.130	0.787	0.051	0.056	0.069
567	Pre	0.499	0.482	0.086	0.596	0.205	0.056	0.100
567	Post	0.498	0.350	0.124	0.783	0.057	0.056	0.066
678	Pre	0.499	0.376	0.074	0.494	0.259	0.077	0.127
678	Post	0.493	0.284	0.116	0.782	0.058	0.054	0.067

As indicated in Table 2, the composition of the pre-pandemic and post-pandemic samples differs, largely due to differences in the participation of school districts in the two periods. Approximately 60% to 70% of the students attended the same two school districts in the post- and pre-pandemic periods. One additional district was included in the pre-pandemic sample and three additional districts were included in the post-pandemic sample. As a result, the data set is not well suited for investigation of the effects of the pandemic on student outcomes. Hence, this paper focuses primarily on the relationships between student attendance and SEL. We do, however, consider the degree to which differences in SEL measures in the two periods could potentially account for differences in attendance between these two periods.

Tables 4 reports mean statistics for all four SEL variables for each pre- and post-pandemic cohort. Figures 1a to 1b display these means graphically. As discussed above, the SEL variables were scaled using the generalized partial credit model (GPCM) developed by Muraki (1992). The SEL measures were constructed using survey item parameters based on a large norming sample of CORE students (Meyer et al, 2018). The SEL measures in the norming sample were centered around zero and the SEL measured in this study are also approximately centered around zero. Later in the paper we report on the variance-covariance structure of the SEL variables.

Table 4a. Average Social Emotion Learning by Cohort, Year, and Pandemic Period

Cohort		**Self Efficacy (SE)**				**Self Management (SM)**		
Grade Span	**Pandemic Period**	**t = 1**	**t = 2**	**t = 3**		**t = 1**	**t = 2**	**t = 3**
456	Pre	-0.071	-0.047	-0.051		-0.017	-0.025	-0.047
456	Post	-0.272	-0.291	-0.289		-0.165	-0.236	-0.361
567	Pre	-0.056	-0.039	-0.022		-0.004	0.007	0.043
567	Post	-0.292	-0.275	-0.219		-0.152	-0.268	-0.258
678	Pre	0.075	0.052	0.073		0.132	0.127	0.096
678	Post	-0.293	-0.186	-0.104		-0.271	-0.208	-0.184

Table 4b. Average Social Emotion Learning by Cohort, Year, and Pandemic Period

Cohort		**Growth Mindset (GM)**				**Social Awareness (SA)**		
Grade Span	**Pandemic Period**	**t = 1**	**t = 2**	**t = 3**		**t = 1**	**t = 2**	**t = 3**
456	17-18	-0.179	-0.013	0.029		0.006	0.049	0.034
456	23-24	-0.481	-0.466	-0.506		-0.251	-0.281	-0.258
567	17-18	-0.189	-0.049	0.077		0.027	0.11	0.149
567	23-24	-0.435	-0.451	-0.371		-0.206	-0.2	-0.031
678	17-18	-0.068	0.099	0.163		0.178	0.252	0.276
678	23-24	-0.46	-0.337	-0.221		-0.163	0.019	0.132

Figure 1a. Average Self Efficacy by Grade Cohort Over Time: Pre- and Post-Pandemic

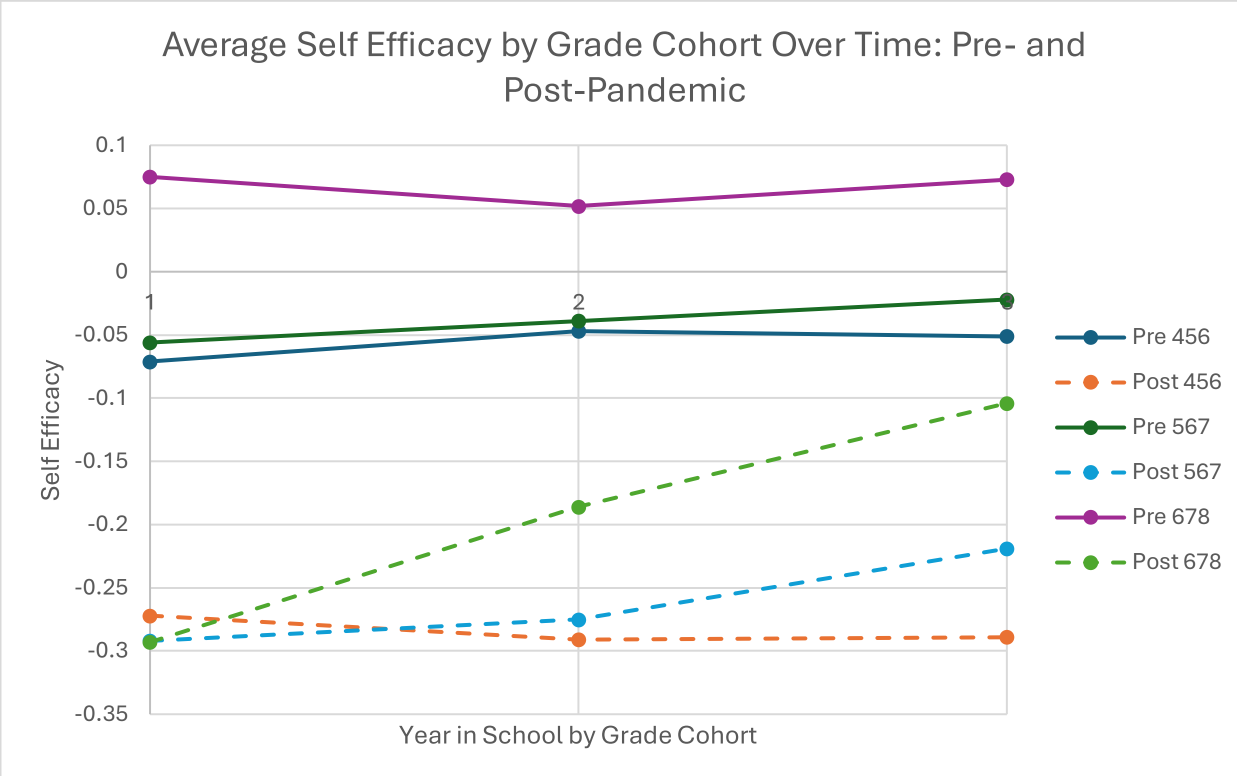


Figure 1b. Average Self Management by Grade Cohort Over Time: Pre- and Post-Pandemic

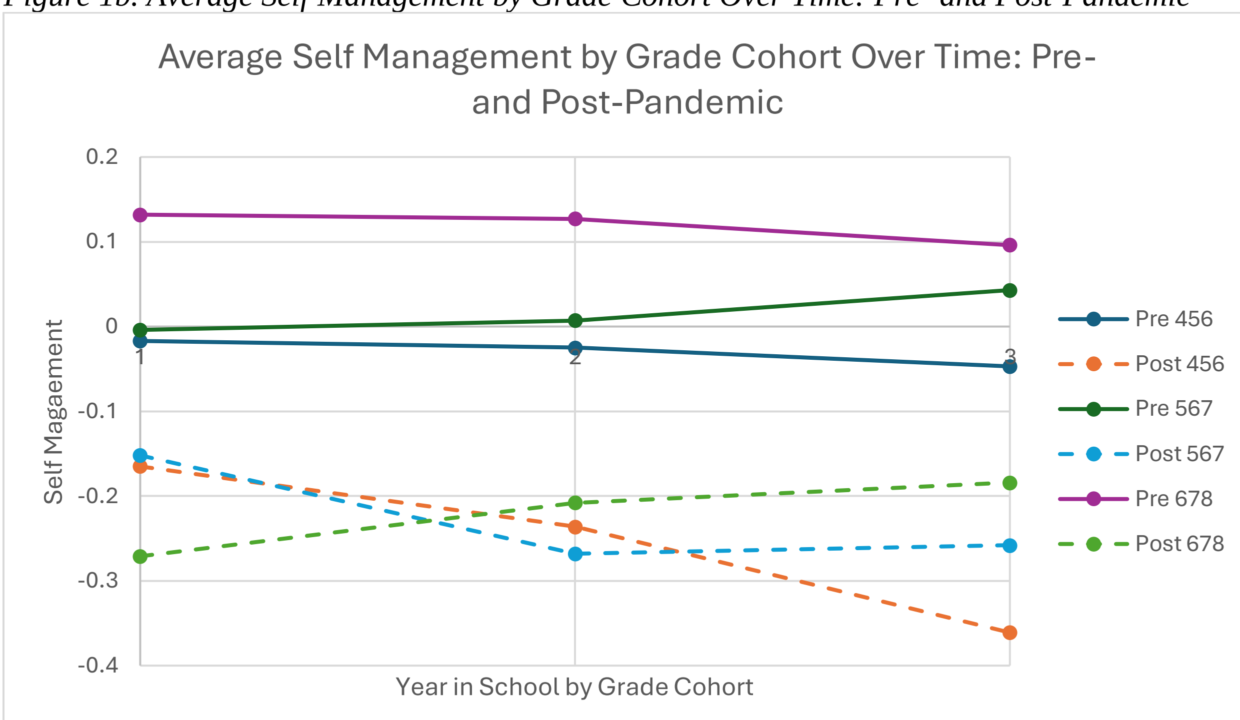


Figure 1c. Average Growth Mindset by Grade Cohort Over Time: Pre- and Post-Pandemic

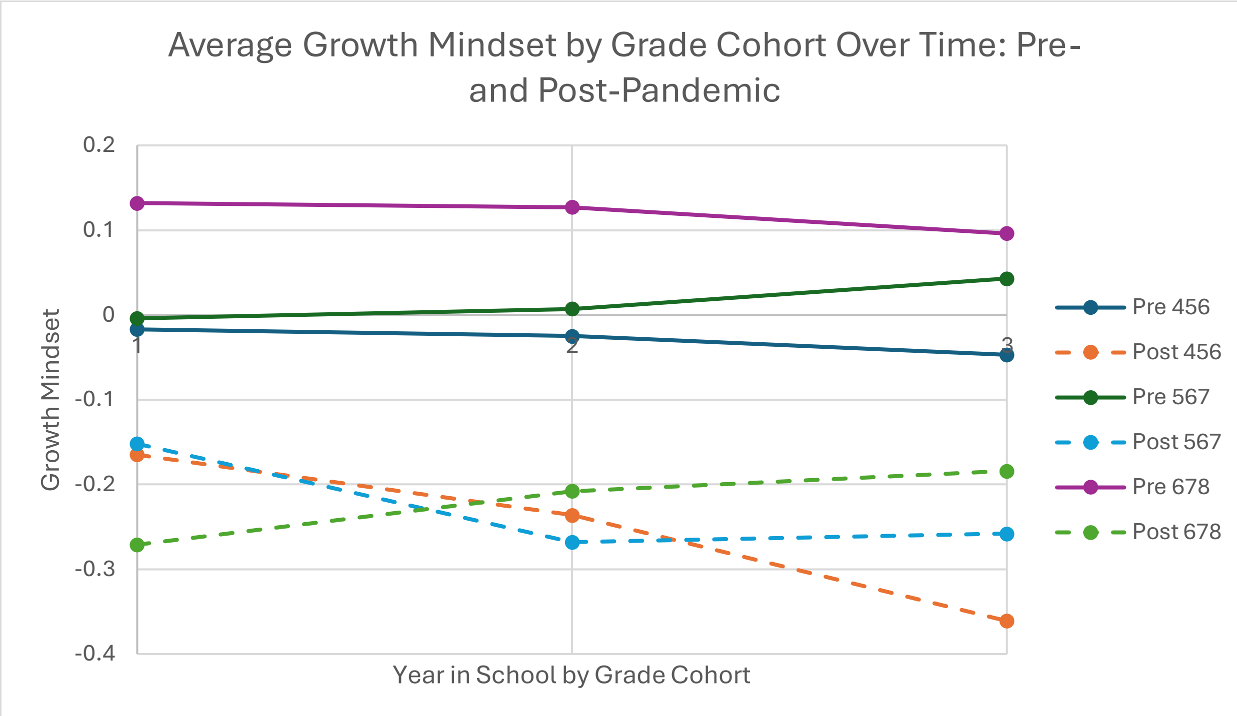
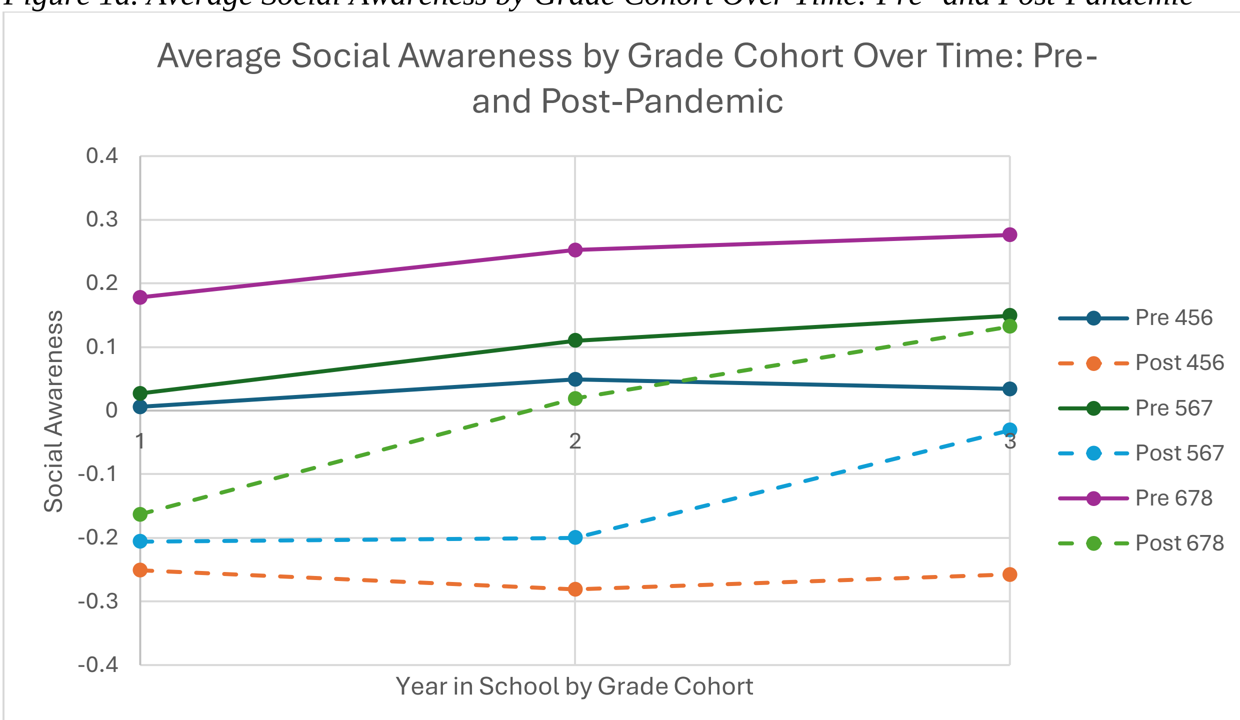


Figure 1d. Average Social Awareness by Grade Cohort Over Time: Pre- and Post-Pandemic



As indicated in the tables and figures, average SEL was substantially lower for the students in the post-pandemic sample compared to the pre-pandemic sample. Some of these differences could be due to differences in the composition of the two samples, but we conjecture that these differences primarily reflect genuine declines in SEL between the two periods. The patterns over time were broadly similar for all cohorts with the exception that average self-efficacy and social awareness increased over time for the grade 678 cohort in the post-pandemic period.

Table 4 reports sample means for two alternative student attendance variables, a transformed measure and a raw, untransformed measure. The motivation for the transformed measure is twofold, one practical and one theoretical. The practical issue is that, as indicated in Figure 2, the distribution of the raw attendance rate is highly asymmetric. Models of skewed variables can be used in practice to capture the mean relationship between skewed outcomes and model predictors, but they are not designed to capture the (at least approximately true) data generating process (DGP). In models where the dependent variable is highly skewed it is common to transform the variable so that its distribution is more symmetric and approximately normally distributed. We consider below a theoretical motivation for transforming the raw attendance measure.

Figure 2. Distribution of the Annual Student Attendance Rate and Transformed Attendance Rate in Grades 4 – 8 Combined

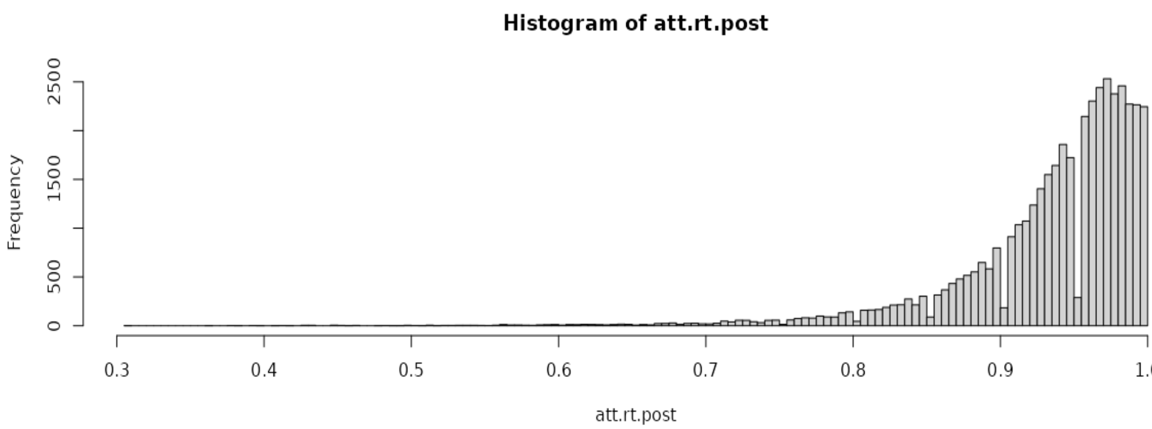
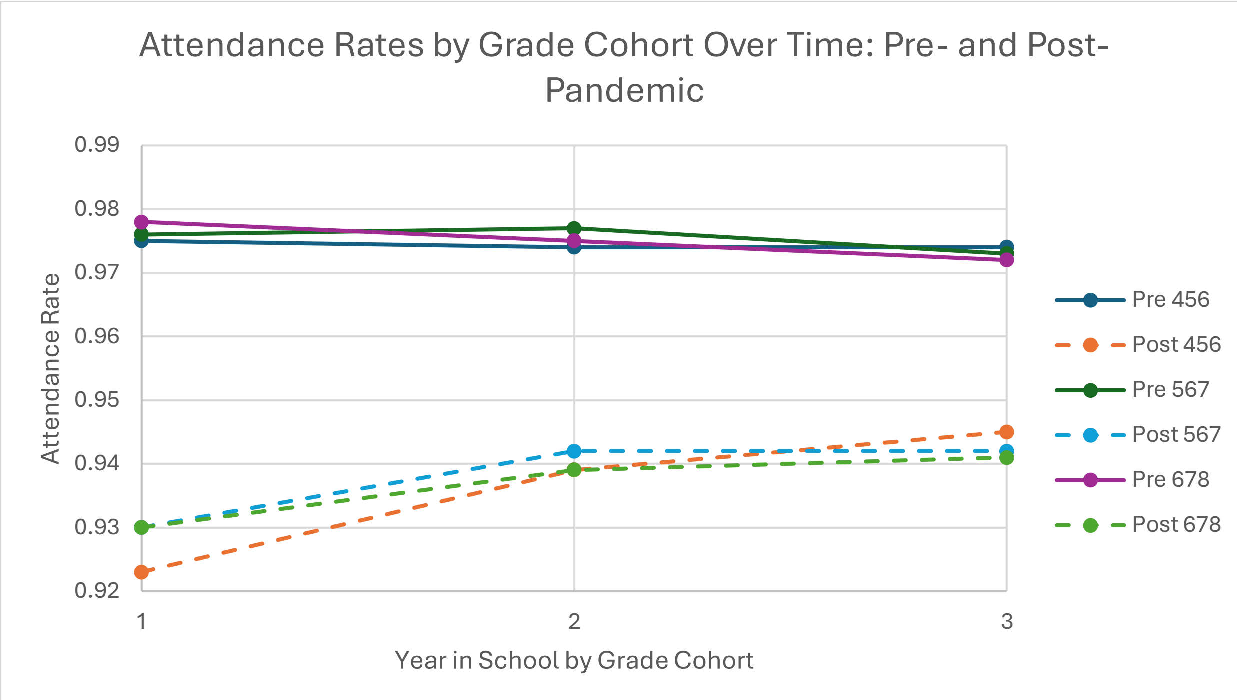


Table 5. Average Student Attendance Rate and Transformed Attendance Measure: Pre- and Post-Pandemic Periods

Cohort		**Attendance Rate**			**Transformed Attendance Measure**		
Grade Span	**Final Year**	**t = 1**	**t = 2**	**t = 3**	**t = 1**	**t = 2**	**t = 3**
456	Pre	0.975	0.974	0.974	2.11	2.10	2.11
456	Post	0.923	0.939	0.945	1.58	1.70	1.77
567	Pre	0.976	0.977	0.973	2.12	2.16	2.10
567	Post	0.930	0.942	0.942	1.63	1.74	1.76
678	Pre	0.978	0.975	0.972	2.17	2.13	2.08
678	Post	0.930	0.939	0.941	1.64	1.72	1.75

Figure 3 displays sample means for the raw attendance rate variable.

Figure 3. Average Student Attendance Rates by Grade Cohort Over Time: Pre- and Post-Pandemic



Like the results for the SEL variables, student attendance rates were substantially lower in the post-pandemic period, compared to the pre-pandemic period and there was a modest increase in attendance rates over the three panel data years in the post-pandemic period. The attendance patterns were essentially identical for all three grade cohorts. Given the similarity in the patterns over time of SEL and student attendance, we will focus in this paper primarily on pre- and post-pandemic models that pool the three grade cohorts. The results were quite like models based on separate grade cohorts.

Methods

We develop a model of student attendance in two parts. We first specify the left-hand side (LHS). Second, we specify the right-hand side (RHS) model, which is designed to support all models for all outcomes where the model can be expressed as a linear or generalized linear model.

Policy discussions of student attendance often focus on the chronic absenteeism, a binary measure of the student attendance rate.[2] Chronic absenteeism is typically defined as an

[2] As examples, Attendance Works and the Annie E. Casey Foundation use chronic absenteeism as the focal point of student attendance policy; Home - Attendance Works; Chronic Absenteeism in U.S. Schools Rose During Pandemic — and Hasn't Recovered - The Annie E. Casey Foundation (aecf.org). Chronic absenteeism measures typically count all types of absences: excused, unexcused, and suspensions.

absenteeism rate greater than or equal to 10% or, equivalently, an attendance rate less than or equal to 90%.[3] A binary chronic absenteeism model could be estimated using a standard logit or probit model, but we have instead constructed a model that makes full use of the distribution of student attendance rates. The disadvantages of focusing only on chronic absenteeism are twofold. One, the analysis and models fail to address different levels of attendance, for example, severe absenteeism (say, attendance less than 85%), near chronic absenteeism (attendance greater than 90% but less than 95%), and very high attendance (attendance greater than or equal to 98%). Two, the models based on binary measures of an underlying continuous variable discard a large amount of information and thus yield parameter estimates that are much less precise than models that exploit the full range of the variable.

We develop a model of student attendance that we treat as an approximation of the true data generating process. In turn, we show how the model can be used to assess the effects of predictors on attendance for students with different expected levels of attendance and chronic absenteeism.

Student Attendance Rate

The student attendance rate differs from an achievement outcome in two major respects. First, whereas student achievement is a cumulative measure that grows over time, student attendance is a non-cumulative student outcome. Student attendance rates are correlated over time primarily because they are determined by student (and school) factors that are persistent over time, not because prior student attendance causes current and future attendance. Second, the annual student attendance rate is the result of daily binary attendance events. We consider a simple model of the daily attendance outcome and derive insights on how best to construct a measure of the annual rate that best captures the relationship between attendance and predictors of attendance.

The annual attendance rate for student i in year t, R_{it}, is equal to the average of daily binary attendance outcomes, I_{its}:

$$R_{it} = \sum_{s=1}^{s=N} I_{its} / N \tag{1}$$

where s indexes days and N is the number of days in the school year. The expected annual attendance rate equals the average of daily attendance probabilities:

$$E[R_{it}] = E\left[\sum_{s=1}^{s=N} I_{its}\right] / N = \sum_{s=1}^{s=N} P_{its} \tag{2}$$

[3] The 10% rate corresponds to 18 days absent over the entire school year (or 2 days per month) given a school year with of 180 days and nine months. The NAEP chronic absenteeism measure covers a shorter time frame and is based on students missing three or more days of school in the last month.

where P_{its} = the daily attendance probability. In a model that includes annual but not daily student predictors, represented by the latent variable A_{it}, daily attendance probabilities are the same for each day and are given by:

$$P_{its} = P_{it} = \Pr\left[A_{it} + r_{its} > 0\right] = \Phi\left[U_{it}\right] \tag{3}$$

where we assume that r_{its}, the random (unknown) determinants of daily attendance are normally distributed. This assumption yields a probit model of daily attendance, where $\Phi[.]$ represents the standard normal cumulative distribution function. (The next section presents a model of A_{it}.)

Given the large number of days in the school year (typically $N \approx 180$), the annual attendance rate is a very precise estimate of the daily attendance probability:

$$R_{it} \approx P_{it} = \Phi\left[A_{it}\right] \tag{4}$$

Taking the inverse of the standard normal CDF yields an attendance outcome A_{it} which is a transformed measure of the attendance rate R_{it}:

$$A_{it} \equiv \Phi^{-1}\left[R_{it}\right] \tag{5}$$

Using the transformed attendance variable in place of the attendance rate allows us to model attendance using linear models (of the latent variable A_{it}) and is thus akin to a generalized linear model (GLM, McCullagh and Nelder, 1989). The standard normal CDF used to construct the transformed attendance variable operates, as in a GLM, as a link function.[4]

The Right-Hand Side of the Model

The RHS model specifications implement a quasi-experimental panel data model to address the relationships between social emotional learning competencies (SEL) and annual student attendance. We consider predictive analytics applications of the model in early warnings systems and model design and assumptions that justify interpretation of parameter estimates as causal. Although panel data models tend to focus on changes over time in outcomes and predictors, we develop a model that decomposes the effects of SEL into transitory (within variance) and school average (between variance) components.

[4] One of the technical issues with transforming the attendance rate using, for example, the probit or log odds functions, is that the functions fail for outcomes equal to 100%. (The function conceptually returns a value equal to positive infinity.) The standard practical solution to this problem is to convert value 1.00 to a slightly lower value, for example, 0.995. In our study, only a small proportion of attendance rates equal 1.00, so the arbitrary choice of the slightly lower value has minimal effect on the estimates. One interesting alternative approach to address the issue of skewness and values equal to 0 or 1 is to split the attendance rate into multiple discrete levels and use an ordered probit or logit model instead of a linear model. This approach allows direct modeling of different levels of attendance and chronic absenteeism. Papay and Wooldridge (1995) consider a model like the model presented in the text. Liu and Loeb (2021) address the skewness in the attendance rate distribution and the fact that days absent is literally a count measure using the negative binomial regression model (NBRM),

Panel Data Models

We develop panel data models of student attendance in three phases. First, we consider two closely related panel data models: the fixed effects (FE) and correlated random effects (CRE) models. Fixed effect models, as opposed to random effects (RE) models, control for the possibility that predictors are correlated with unobserved student effects. CRE models drop fixed effects from the model and explicitly model the correlation between effects and average student predictors. CRE models are important for our purposes because they provide estimates of the effects of stable (between variance) and transitory (within variance) predictors. We state the conditions under which the estimated parameters in the FE and CRE models can be interpreted as estimates of causal parameters.

Second, we investigate whether the properties and interpretations of the FE and CRE models are affected by whether the predictors hold if the SEL variables are generated by two (or multiple) factors rather than a single factor. This issue could be salient given that SEL is measured in our study (and in most contexts) using a student survey, as discussed above. If SEL constructs are partly multidimensional, survey responses may reflect multiple factors. Indeed, the surveys (or different items in the surveys) may simultaneously capture stable and transitory components of SEL.

Third, we consider whether the proper measure of average SEL is the standard average of student data or a hypothetical latent measure of a stable factor. In short, we consider whether the average variable is measured with error relative to the hypothetical latent measure. We demonstrate how to control that type of measurement error.

A Linear Panel Data Model of Student Achievement Gain and Attendance

The panel data model presented in this section is designed to handle any outcome variable that can be modeled using a model that is linear in the predictors. Let A_{it} represent the dependent variable in the model for student *i* in school year *t* for a single cohort or pooled cohorts.

A standard method of controlling for selection bias in panel data models due to student heterogeneity is to include student and year fixed effects (FE) in the model (Wooldridge, 2010; Cameron and Trevedi, 2005). Kanopka et al (2024) used this approach in their models of the effects of SEL on attendance and student achievement, although they used a raw, untransformed attendance rate as the dependent linear variable. This model is given by:

$$A_{it} = \eta_{1t} + Z_{it}\lambda + c_i + e_{it} \qquad (6)$$

where

Z_{it} = row vector of time-variant predictors (SEL variables)

λ = column vector of coefficients on SEL variables

η_{1t} = year-in-school effect, crossed with cohort status in pooled model

c_i = fixed student effect, centered around zero

e_{it} = student-by-year error component

The heterogenous student effect c_i is potentially correlated with all predictors, including SEL. Indeed, although the effect is often treated as a nuisance parameter and only included in models to allow consistent estimation of the within slope parameter λ, we are interested in the degree to which the effect is correlated with student average SEL (or the stable SEL component), as is explained below. Estimation of the panel data model using fixed effects (or correlated random effects), yields consistent parameter estimates given the assumption that the time-variant variables Z_{it} in each year are uncorrelated with the student-level errors e_{it} in each year, the assumption of strict exogeneity (Wooldridge, 2010, p. 288).

The model with fixed effects can also be modified to difference out the student effect, which yields the first difference (FD) model:

$$(A_{it} - A_{it-1}) = (\gamma_t - \gamma_{t-1}) + (Z_{it} - Z_{it-1})\lambda + (e_{it} - e_{it-1}) \tag{7}$$

This model formulation makes it clear that the effects of SEL and other time-variant variables are estimated off the change in these variables; that is, the transitory components.[5]

Although the panel data model can be estimated including fixed effects or by differencing out the fixed effects, we modify the model so that the student effect c_i can be decomposed into two parts, a component that is correlated with average student characteristics and a random student-level component. The two components are closely related to the stable and transitory components considered above. This model is the correlated (conditional) random effects (CRE) specification developed by Mundlak (1978) and Chamberlain (1982, 1984).[6] In linear models, Mundlak (1978) demonstrated that fixed effects and CRE model specifications yield equivalent model estimates of the slope parameters. The CRE models is obtained by specifying an equation for the student effect, given means of the time-variant predictors for each student and time-invariant student demographic characteristics, and substituting that equation into the panel data model. The CRE equation is given by:

$$c_i = \eta_2 + \bar{Z}_{i\bullet}\delta + X_i\beta + u_i \tag{8}$$

where

X_i = row vector of variables that do not vary over time such as demographic variables

$\bar{Z}_{i\bullet}$ = row vector of student level means of the time-variant predictors, where the bar indicates a mean and the dot replaces the *i* subscript.

β, δ = column vector of coefficients

η_2 = model intercepts, including year by cohort effects

[5] Note that the model does not include lags of the student outcomes – student attendance or test score gain – as predictors, given inclusion of the heterogeneity effect c_i. Kanopka (2024) also exclude prior outcomes from their fixed effects models. Some teacher value-added models of attendance include prior attendance as a predictor under the logic that these models should maximize predictive power to control for factors that are pre-determined and thus could not have been caused by the current teacher. In these models, the coefficients on the control variables are not intended to be interpreted as causal (Gershenson, 2016; Jackson, 2018); the focus is on estimation of teacher effects.

[6] Wooldridge (2010, Sections 15.8.2, 15.8.3, 16.3.4) provides an excellent summary of fixed effects and correlated random effects models. See also Wooldridge (2019).

u_i = random student-level error, which corresponds to a level-2 error in a multilevel model

The CRE equation splits the student effect into a correlated component $X_i\beta + \bar{Z}_{i\bullet}\delta$ () and a random effect u_i. Substituting this equation into the fixed effect model yields:

$$A_{it} = \eta_t + Z_{it}\lambda + \bar{Z}_{i\bullet}\delta_1 + X_i\beta + u_i + e_{it} \tag{9}$$

where the two intercept parameters are combined: $\eta_t = \eta_{1t} + \eta_{2t}$. The CRE model can be estimated as a standard random effects model, given the inclusion of the mean and time invariant student variables. The CRE model can be rewritten to highlight the difference between the effects of the observed transitory and student-average components:

$$A_{it} = \eta_t + (Z_{it} - \bar{Z}_{i\bullet})\lambda + \bar{Z}_{i\bullet}\kappa + X_i\beta + u_i + e_{it} \tag{10}$$

where $(Z_{it} - \bar{Z}_{i\bullet})$ represents the observed transitory (deviation from mean) component and $\kappa = \lambda + \delta$ is the coefficient on the student average variable. The coefficients λ, κ represent the within-student variance and between-student variance effects of SEL, respectively.

There are two strong advantages to using the CRE model instead of (or in addition to) the FE model. One, the CRE specification is more flexible because it can be used in both linear and nonlinear models, such as binary and ordered probit models that focus on different levels of attendance and chronic absenteeism. Using fixed effects in these nonlinear models creates the "incidental parameters" problem: Nonlinear models that include fixed effects produce inconsistent parameter estimates for fixed numbers of student observations over time (Wooldridge, 2010, p. 612). In short, we are interested in using a model specification that can be applied to both linear regression and nonlinear models since some student outcomes are best modelled using nonlinear models.

Two, the CRE model provides estimates of the effects of the student average and transitory variables. Both variables can be used in early warning systems to provide predictions of future student outcomes.[7] See, for example, Meyer et al (2024).

How should the coefficients on the student average and transitory variables be interpreted? It is standard practice in FE and CRE models to treat the student heterogeneity effect c_i and the predictors of that effect as nuisance variables and parameters that are included solely to allow consistent estimation of the within-student slope parameter λ. These models yield consistent parameter estimates given the assumption that the time-variant variables Z_{it} in each year are uncorrelated with the student-level error e_{it} in each year, the assumption of strict exogeneity (Wooldridge, 2010, p. 288). Strict exogeneity would be violated, for example, if: (1) the time-variant predictors (SEL) are measured with error or (2) the true model includes a causal time-variant variable that is correlated with changes in SEL but is omitted from the model. Estimates

[7] We modify the model slightly to provide operational predictive analytics based on the most recent student data. We replace the student mean variable with means based on prior years of data, whereas in the panel data model student means are based on all (past and future) panel data.

of the reliability of the SEL variables used in this study indicate that the reliabilities are quite high (Meyer, 2018). If strict exogeneity is violated due to the omission of time-variant variables the fallback interpretation of the within-student parameter is that it is an upper bound on the true causal effect if the bias due to omitted time-variant is hypothesized to be positive.[8]

Similar logic applies to the estimates of the between-student parameter: $\kappa = \lambda + \delta$. If the model excludes time-invariant variables (or the means of time-variant variables) that are predictive of average student outcomes and correlated with average SEL, the student-level error term u_i is correlated with $\bar{Z}_{i\bullet}$ and estimates of the between-student parameter will be biased. Our model mitigates this possibility to some degree by including invariant student demographic variables (X) in the model. As above, the fallback interpretation of the between-student parameter is that it is an upper bound on the true causal effect if the bias due to omitted time-invariant variables is hypothesized to be positive.

One of the implicit assumptions of the FE and CRE models is that the effects of time-variant variables can (and should) be estimated solely from changes in these variables. If the student effect c_i is not correlated with average student predictors (in which case, $\delta = 0$ and $\lambda = \kappa$, more efficient estimates cab be obtained from the random effects (RE) model (Hsiao, 2014). Mundlak (1978) argued that there is typically no justification for assuming the student effect is random (see also Hsiao, 2014, pp. 48-56). However, as discussed below, this conclusion is based on the implicit assumption that the true effects of stable (average student) and transitory components are identical. We consider below a model that investigates this assumption.[9]

A Hypothetical Two-Factor Model of the Data Generating Process of Predictors (SEL)

In this section we develop a hypothetical two factor model of SEL to understand how interpretation of panel data model parameters is affected by the data generating process of measured SEL. We extend the CRE model to include two SEL vectors, rather than a single vector of SEL variables and derive formulas for the parameters if modeled using a single factor (as considered above). We simplify the model by dropping model intercepts, year-in-school effects, and time-invariant demographic variables and we specify the student effect and student-by-year error as random and uncorrelated with the predictors. The model with two SEL factors is given by:

$$A_{it} = Z_{1it}\lambda_1 + Z_{2it}\lambda_2 + w_i + f_{it} \tag{11}$$

and, equivalently, by:

$$A_{it} = (Z_{1it} - \bar{Z}_{1i\bullet})\lambda_1 + (Z_{2it} - \bar{Z}_{2i\bullet})\lambda_2 + \bar{Z}_{1i\bullet}\lambda_1 + \bar{Z}_{2i\bullet}\lambda_2 + w_i + f_{it} \tag{12}$$

---

[8] Note that it is important to be strategic in including additional variables in the model. It is inappropriate to include variables that are caused by SEL since inclusion of these variables yields underestimates of the effects of SEL. It is not a problem if variables that cause SEL are excluded from the model if the SEL variables (however generated) cause student outcomes. We are not subject to either concern because the SEL variables are the only time-variant variables included in the model.

[9] Hill et al (2020) consider additional potential limitations of fixed effects models for panel data.

where

Z_{1it} , Z_{2it} = row vectors of two SEL factors

$(Z_{1it}-\bar{Z}_{1i\bullet}),(Z_{2it}-\bar{Z}_{2i\bullet})$ = row vectors of the transitory (deviation from mean) components for the two factors

λ_1, λ_2 = column vectors of coefficients on twin SEL factors

w_i = random uncorrelated student effect, centered around zero

f_{it} = student-by-year error component

Equation (12) highlights the fact that the coefficients on the transitory and student average variables are identical. This is due to the assumption that the student effect w_i is random. Hence, we start with a model in which the effects of the transitory and student average predictors are identical and causal, given the maintained assumptions. As a result, estimation of the causal effects of SEL can be based solely on transitory (within) variance using a FE or CRE model or preferably, a random effects model. In contrast, in the one factor CRE model presented above – equation (10) – the coefficients on the transitory and student average variables differ, in principle, and we ask the question of whether there is distinct information on the causality of SEL from both transitory and between-student variance components. To address this question, we derive formulas for the parameters if the single factor CRE model given the assumptions of the model with two factors. To simplify the analysis, we consider below the case of a single SEL variable.

To derive the required parameter formulas, we treat the predictors in the two-factor model given by equation (12) as omitted variables (since they are not observed) and construct auxiliary regressions of these variables given the observed variables in the one factor model given by equation (10):

$$\begin{aligned}(Z_{1it}-\bar{Z}_{1i\bullet}) &= (Z_{it}-\bar{Z}_{i\bullet})a_1+q_{1it}\\ (Z_{2it}-\bar{Z}_{2i\bullet}) &= (Z_{it}-\bar{Z}_{i\bullet})a_2+q_{2it}\end{aligned} \tag{13}$$

$$\begin{aligned}\bar{Z}_{1i\bullet} &= \bar{Z}_{i\bullet}b_1+r_{1i}\\ \bar{Z}_{2i\bullet} &= \bar{Z}_{i\bullet}b_2+r_{2i}\end{aligned} \tag{14}$$

We derive formulas for the auxiliary regression coefficients given the following assumptions. Z is the sum of the two factors[10]:

$$Z_{it}=Z_{1it}+Z_{2it} \tag{15}$$

The two factors have equal variance and, as in standard factor analysis models, are uncorrelated:

[10] In general, auxiliary omitted variable bias equations include all regressors included in the model. However, in our panel data model we have separated the time-variant SEL variables into within and between variance variables, which are uncorrelated by construction. As a result, the auxiliary regressions for the within-variance equations need only include the corresponding within-variance regressors. Similarly, the auxiliary regressions for the between-variance equations need only include the corresponding between-variance regressors.

$$\omega^2 = Var[Z_{1it}] = Var[Z_{2it}] \tag{16}$$

The two factors (and the summed factor Z) have a standard variance components structure, as in equation (19), with intraclass correlation coefficients (ICCs) equal to ρ_1 and ρ_2, respectively. Given this assumed structure, the formulas for the auxiliary regression coefficients are given by:

$$\begin{aligned}
a_1 &= (1-\rho_1)/[2-\rho_1-\rho_2] \\
a_2 &= 1-a_1 \\
b_1 &= [\rho_1+(1-\rho_1)/T]/[\rho_1+\rho_2+(1-\rho_1-\rho_2)/T] \\
b_2 &= 1-b_1
\end{aligned} \tag{17}$$

Note that the formulas for the "*a*" parameters do not depend on *T*, the length of the panel. The formulas for the "*b*" parameters depend on *T*, but not to a large degree.

Finally, we obtain the CRE parameter formulas for the single factor model given the two-factor model by substituting the auxiliary omitted variable bias equations into the two-factor model, which yields the following formulas:

$$\begin{aligned}
\lambda &= a_1\lambda_1 + a_2\lambda_2 \\
\kappa &= \lambda + \delta = b_1\lambda_1 + b_2\lambda_2 \\
\delta &= (b_1-a_1)\lambda_1 + (b_2-a_2)\lambda_2 \\
u_i &= r_{1i}\lambda_1 + r_{2i}\lambda_2 + w_i \\
e_{it} &= q_{1it}\lambda_1 + q_{2it}\lambda_2 + f_{it}
\end{aligned} \tag{18}$$

Equations (17) and (18) imply the following key results:

- The student effect u_i and student-by-year error f_{it} are random and uncorrelated with the predictors, a result that carries over from the maintained two-factor model. Hence, the transitory (within) and student average (between) coefficients in the one-factor model are both causal parameters, given then maintained assumptions.
- The transitory (within) and student average (between) coefficients are weighted averages of the hypothetical coefficients λ_1 and λ_2.
- The transitory (within) parameter λ entirely reflects the effects of the transitory variances of the two factors, given that the weights a_1 and a_2 are a function of one minus the intraclass correlations coefficients (which measure the relative magnitude of the transitory components).
- The student average (between) parameter primarily reflects the effects of the stable parts of the two factors but also captures part of the transitory effects unless the number of years (*T*) is large.

As stated previously, we are interested in whether there is distinct information on the causality of SEL from both the transitory and between student variance components. This is a moot question in the hypothetical two-factor model given that the effects of the transitory and between-student variance components are identical. Does this finding carry over to the single factor model given that the single factor is an exact combination of the two factors? In other words, does $\lambda = \kappa$?

Table 6 reports values for the coefficients in the one-factor CRE model, given hypothetical values of the parameters in the two-factor model:

- transitory (within variance) coefficient: λ
- stable, average student (between variance) coefficient: κ
- difference in coefficients: $\delta = \kappa - \lambda$

Table 6. Coefficients on Transitory (λ) and Stable (κ) Components Given Two-Factor Data Generating Process and Hypothetical Parameters

λ_1	λ_2	ρ_1	ρ_2	**a1**	**a2**	**b1**	**b2**	λ **Within**	κ **Between**	$\delta = \kappa - \lambda$ **Difference**	**Comment**
1	0.2	0.50	0.50	0.50	0.50	0.500	0.500	0.600	0.600	**0.000**	Equal ICC: ρ
0.2	1	0.50	0.50	0.50	0.50	0.500	0.500	0.600	0.600	**0.000**	Equal ICC: ρ
											λ & ρ
1	0.2	1.00	0.50	0.00	1.00	0.600	0.400	0.200	0.680	**0.480**	Hi/Hi
1	0.2	0.75	0.25	0.25	0.75	0.625	0.375	0.400	0.700	**0.300**	Hi/Hi
0.2	1	0.50	1.00	1.00	0.00	0.400	0.600	0.200	0.680	**0.480**	Lo/Lo
0.2	1	0.25	0.75	0.75	0.25	0.375	0.625	0.400	0.700	**0.300**	Lo/Lo
1	0.2	0.50	1.00	1.00	0.00	0.400	0.600	1.000	0.520	**-0.480**	Hi/Lo
1	0.2	0.25	0.75	0.75	0.25	0.375	0.625	0.800	0.500	**-0.300**	Hi/Lo
0.2	1	1.00	0.50	0.00	1.00	0.600	0.400	1.000	0.520	**-0.480**	Lo/Hi
0.2	1	0.75	0.25	0.25	0.75	0.625	0.375	0.800	0.500	**-0.300**	Lo/Hi

As indicated in Table 6, the transitory (within) and student average (between) parameters are not, in general, equal. Indeed, as indicated in the table and based on inspection of the parameter formulas, the two parameters are equal if the effects of the two factors are identical: $\lambda_1 = \lambda_2$; or if the intraclass correlation coefficients are equal: $\rho_1 = \rho_2$. If the pair of parameters, (λ_1, ρ_1) are both relatively high (Hi/Hi) or relatively low (Lo/Lo), the student average (between) parameter exceeds the transitory/within parameter: $\kappa > \lambda$ and $\delta > 0$ [11]. If the opposite is true (Hi/Lo or Lo/Hi), the transitory parameter exceeds the stable parameter: $\lambda > \kappa$ and $\delta < 0$. In the first case, the dominant effect of SEL is via the student average (between) variable.

The key finding of this exercise is that both transitory (within) and student average (between) parameters may differ, *and* they may provide valid and distinct information on the causal effect of the predictors. That is the case in the example considered above. It is thus questionable to focus exclusively on the transitory (within) parameter under the assumption that it alone provides information on the causal effects of SEL or other time-variant variables, given the assumption of strong exogeneity. We repeat the conclusion stated earlier: it is sensible to interpret the within-

[11] The Hi/Hi and Lo/Lo parameters yield the same results due to fact that the two factors are interchangeable hypothetical factors.

and between-variance parameters as upper bound estimates of the true causal effects if the bias due to omitted time-variant and time-invariant variables is hypothesized to be positive. This logic supports our decision to use the CRE model to report on both the transitory (within) and student average (between) parameters.

How to Control for Error in Reported Student SEL? What is the Proper Measure of Average, Between-Variance SEL?

In this section we consider how to address two very different types of measurement error: (1) Statistical error, error due to unreliability in measured SEL as a measure of SEL over the school year and (2) Conceptual error, error in student average SEL as a measure of the stable component of SEL. We address these issues using the following multivariate variance components model of the four SEL variables given by:

$$Z_{pit} = \mu_{pt} + F_{pi} + H_{pit} + v_{pit} \tag{19}$$

where
p indexes the time-variant variables (SEL variables), *i* indexes students, and *t* indexes years in school
Z_{pit} = time-variant student predictor *p*
F_{pi} = stable student effect for predictor *p*
H_{pit} = transitory student-by-year effect for predictor *p*
v_{pit} = measurement error
μ_{pt} = predictor-by-year intercept

Alternative models could allow for a more complex statistical structure (for example, one that allows for serial correlation), but the standard variance components model is adequate for our purposes given that the length of the panel is short (3 years). In the remainder of this paper, we in most cases drop the predictor subscript *p* and treat variables as vectors and matrices, where appropriate.

Statistical error: v_{it}. The first type of measurement arises potentially from several sources. One, the number of survey items used to measure each SEL construct is limited; Appendix A reports that each SEL construct is measured using only four or five items. Cronbach's coefficient alpha is commonly used to measure the internal consistency reliability of survey or test items. As reported in Meyer, Wang, and Rice (2018) using data from the 2015-16 school year, Cronbach's coefficient alpha ranges from 77% to 89% in grades 4 to 8 for self-efficacy, self-management, and social awareness and from 64% to 75% for growth mindset (measured using the negatively worded items). Two, student responses each year were obtained from a single survey administration and thus may reflect error variation due to day and time-specific conditions. Cronbach's coefficient alpha does not capture this source of error. Three, survey items for a given construct could measure more than a single attribute, as considered in the previous section. In this case, inconsistency in survey responses could partly reflect multidimensionality of the construct rather than error.

Given that we do not have access to a gold standard measure of SEL (measured without error) and given uncertainty about the exact source and magnitude of error, we adopt the following strategy. We assume that statistical measurement error (from all sources) is additive (classical error), nondifferential, and can be treated as approximately homoscedastic. We report estimates for a single baseline reliability equal to 85% for all four SEL constructs, *and* we evaluate the robustness of the estimates for a wide range of reliabilities. Since day/time-specific error may affect all responses on the SEL survey we also consider error structures that allow for correlated error (a step that is not typically explored). The estimation strategy presented below facilitates rapid exploration of the consequences of different assumptions about the magnitude and structure of statistical measurement error.

Conceptual error: $\bar{H}_{i\bullet}$. If, as argued above, the student average variable $\bar{Z}_{i\bullet}$ potentially captures valid information on the effects of SEL on student outcomes (and serves as more than a control variable in the CRE model), the following conceptual question arises: is the proper measure of the average, between-variance SEL variable the hypothetical stable component of SEL (F_i in equation (19)) rather than the average based on the limited number of years in a given panel data set? One of the advantages of prioritizing the effect of the stable component is that it is well defined given the assumption that the distribution of the SEL variables is well-captured by a multivariate variance components model of equation (19). In contrast, the structure of the student average varies directly with the length of the longitudinal panel. In large panels, the student average approximately equals the stable component, whereas in short panels the student average is measured with error as a measure of the stable component. Unlike the case of statistical error, panel data provides the necessary information to compute the variance of error in average SEL as a measure of the stable SEL component.

Below we develop formulas for the bias due to statistical and conceptual measurement error and demonstrate how to control both sources of error. The panel data model based on the stable rather than the empirical measure of student average SEL is given by:

$$A_{it} = \eta_t + H_{it}\lambda + F_i\kappa + X_i\beta + u_i^* + e_{it}^* \tag{20}$$

where F_i is the stable variance component and $H_{it} = Z_{it} - F_i$ is the transitory component in equation (19) and u_i^* and e_{it}^* represent student and transitory errors (excluding measurement error). Given the assumption that the distribution of the vector of SEL variables Z_{it} is appropriately captured by a multivariate variance components model, student-average SEL is given by:

$$\bar{Z}_{i\bullet} = F_i + [\bar{H}_{i\bullet} + \bar{v}_{i\bullet}] \tag{21}$$

and transitory SEL (the deviation in SEL) is given by:

$$D_{it} = Z_{it} - \bar{Z}_{i\bullet} = H_{it} + [(v_{it} - \bar{v}_{i\bullet}) - \bar{H}_{i\bullet}] \tag{22}$$

Thus, the measured student average $\bar{Z}_{i\bullet}$ and transitory/deviations $D_{it} = Z_{it} - \bar{Z}_{i\bullet}$ variables are fallible measures of the true stable and transitory parameters, with the errors contained in the terms in brackets. The variance-covariance matrices of these variables are given by:

$$
\begin{aligned}
V_{ZZ} &= Var[Z_{it}] = \Omega_{FF} + \Omega_{HH} + \Sigma_{vv} \\
V_{MM} &= Var[\bar{Z}_{i\bullet}] = \Omega_{FF} + \Omega_{HH} / T + \Sigma_{vv} / T \\
V_{DD} &= Var[Z_{it} - \bar{Z}_{i\bullet}] = \Omega_{HH} (T-1)/T + \Sigma_{vv} (T-1)/T
\end{aligned}
\tag{23}
$$

where

$$
\begin{aligned}
Var[H_{it}] &= \Omega_{HH} \\
Var[F_i] &= \Omega_{FF} \\
Var[v_{it}] &= \Sigma_{vv}
\end{aligned}
\tag{24}
$$

Substituting for the true parameters yields an equation based on the measured, but noisy, predictors and three measurement errors:

$$
A_{it} = \eta_t + (Z_{it} - \bar{Z}_{i\bullet})\lambda + \bar{Z}_{i\bullet}\kappa + X_i\beta - (v_{it} - \bar{v}_{i\bullet})\lambda - \bar{v}_{i\bullet}\kappa - \bar{H}_{i\bullet}(\kappa - \lambda) + u_i^* + e_{it}^* \tag{25}
$$

This equation differs from the typical model with measurement errors in that there are two sets of predictors but three sets of measurement errors. Moreover, the error term $-\bar{H}_{i\bullet}(\kappa - \lambda)$ is multiplied by the difference of the within and between coefficients $(\kappa - \lambda)$. Indeed, this term drops from the equation if the within and between coefficients are identical (the maintained assumption of the random effects model).

To derive the bias formulas, we treat each of the error terms as omitted variables and write auxiliary regressions for the omitted variables, given the observed variables included in the model, $(Z_{it} - \bar{Z}_{i\bullet})$ and $\bar{Z}_{i\bullet}$. This yields:

$$
\begin{aligned}
(v_{it} - \bar{v}_{i\bullet}) &= (Z_{it} - \bar{Z}_{i\bullet})a_1 + r_{1it} \\
\bar{v}_{i\bullet} &= \bar{Z}_{i\bullet}b_1 + X_i b_2 + r_{2i} \\
\bar{H}_{i\bullet} &= \bar{Z}_{i\bullet}c_1 + X_i c_2 + r_{3i}
\end{aligned}
\tag{26}
$$

where a_1, b_1, and c_1 are (*4x4*) parameter matrices, the b_2, and c_2 matrices conform to the dimension of the demographic variables $X_{i\bullet}$, and the equations include residuals r_{1it}, r_{2i}, *and* r_{3i}. The auxiliary equation parameter matrices are not estimated but are constructed (as explained below). Note that the student average variable $\bar{Z}_{i\bullet}$ is not included in the equation for the error deviations variable and similarly, the transitory variable $(Z_{it} - \bar{Z}_{i\bullet})$ is not included in the equations for the error means variables. This stems from the model design: the within and between variance variables are orthogonal. This design simplifies the formulas for the parameters of the auxiliary equations. Note also that whereas as second and third auxiliary regressions include the time-invariant demographic variables, the first auxiliary equation includes no additional time-varying variables. The model could easily be extended to include the latter variables.

Substituting the auxiliary error equations into model yields the following model, defined in terms of the biased parameters:

$$A_{it} = \eta_t + (Z_{it} - \bar{Z}_{i\bullet})\lambda_{bias} + \bar{Z}_{i\bullet}\kappa_{bias} + X_i\beta_{bias} + u_i + e_{it} \tag{27}$$

where[12]

$$\begin{aligned} \lambda_{bias} &= (I - a_1)\lambda \\ \kappa_{bias} &= (I - b_1)\kappa - c_1(\kappa - \lambda) = (I - b_1 - c_1)\kappa + c_1\lambda \\ \beta_{bias} &= \beta - b_2\kappa - c_2(\kappa - \lambda) = \beta - (b_2 + c_2)\kappa + c_2\lambda \end{aligned} \tag{28}$$

As indicated, the bias equations resemble standard results for attenuation bias due to measurement error except that the bias equations depend on the true parameters κ and λ but also on their difference.

Estimation Method. The two most used methods of measure error control (MEC) are errors-in-variables (EV) (Fuller, 1987; Buonaccorsi, 2010) and regression calibration (RC) (Carroll et al, 2006; Spiegelman, McDermott, and Rosner, 1997).[13] Both methods require external information on the magnitude of measurement error. EV is commonly used in social science research and is incorporated into many statistical packages. RC is widely used in biostatistics and epidemiology research. The methods generally yield equivalent results in linear regression models but are implemented quite differently. We correct for measurement error using an approach that is equivalent to EV and RC but operates directly from the biased estimates and corrects those estimates given different assumptions about the magnitude of statistical error and the option to define student average variable either in terms of its empirical value or as a fallible measure of the stable component. Tostenson, Buonaccorsi, and Demidenko (1998) used a similar approach, although their primary focus was on error-corrected estimates of the variance components.

Using this approach, we need only estimate the model once (for a given model specification). We then apply alternative error corrections to the biased model estimates. One advantage of this approach is that it provides insight into the mechanics and impact of the different error corrections.

We obtain the error correction (EC) formulas by solving for the true parameters in equation (26), which yields

$$\begin{aligned} \lambda_{EC} &= [I - a_1]^{-1}\lambda_{bias} \\ \kappa_{EC} &= [I - b_1 - c_1]^{-1}\kappa_{bias} - c_1[I - a_1]^{-1}\lambda_{bias} \\ \beta_{EC} &= \beta_{bias} + (b_2 + c_2)\kappa_{EV} - c_2\lambda_{EV} \end{aligned} \tag{29}$$

The auxiliary regression parameters cannot be directly estimated since the measurement errors are not observed but they can be constructed given information on the variance and covariances

---

[12] The error components equal: $\begin{aligned} u_i &= u_i^* - r_{2i}\kappa - r_{3i}(\kappa - \lambda) \\ e_{it} &= e_{it}^* - r_{1it}\lambda \end{aligned}$.

[13] See, also, the following: Bennett et al (2017), Freedman et al (2008), Gleser (1992), Guo (2011), and Keogh (2014).

of the measurement errors, as is the case with the standard error correction methods. The parameter a_1 is straightforward to construct because the auxiliary equation for this parameter does not include additional predictors. The regression formula for this parameter is given by the matrix version of simple regression:

$$\begin{aligned} a_1 &= Var[Z_{it} - \bar{Z}_{i\bullet}]^{-1} Cov[Z_{it} - \bar{Z}_{i\bullet}, v_{it} - v_{i\bullet}] \\ &= V_{DD}^{-1} \Sigma_{vv} (T-1)/T \end{aligned} \tag{30}$$

where all matrices are (*4x4*) matrices. In our application the number of longitudinal observations is $T=3$. Thus, the multiplier on the error variance-covariance matrix, $(T\text{-}1)/T = 2/3$, is relatively large.

The technique for deriving the formulas for the *b* and *c* parameters is more complicated since the auxiliary regressions for these parameters include an additional set of predictors, the time-invariant student demographic variables. The Frisch-Waugh-Lovell Theorem (Lovell, 1963) provides a simple three-step method for calculating the two sets of parameters in the $\bar{v}_{i\bullet}$ and $\bar{H}_{i\bullet}$ regressions. In the first step $\bar{Z}_{i\bullet}$ is regressed on the time-invariant variables X_i in the following auxiliary regression to purge $\bar{Z}_{i\bullet}$ of its correlation with X_i.

$$\bar{Z}_{i\bullet} = X_i \pi + R_i \tag{31}$$

There is no need to estimate similar regressions for the left-hand side variables, $\bar{v}_{i\bullet}$ and $\bar{H}_{i\bullet}$, since they are uncorrelated with X_i. by design. In the second step, the parameters b_1 and c_1 are constructed using the matrix version of simple regression, where R_i replaces $\bar{Z}_{i\bullet}$ as the right-hand side variable:

$$\begin{aligned} b_1 &= Var[R_i]^{-1} Cov[R_i, \bar{v}_{i\bullet}] \\ &= V_{RR}^{-1} \Sigma_{vv} / T \end{aligned} \tag{32}$$

$$\begin{aligned} c_1 &= Var[R_i]^{-1} Cov[R_i, \bar{H}_{i\bullet}] \\ &= V_{RR}^{-1} \Omega_{HH} / T \end{aligned} \tag{33}$$

where $V_{RR} = Var[R_i]$. In the third step, b_2 and c_2 are constructed given constructed values of b_1 and c_1 and the estimated parameter π:

$$\begin{aligned} b_2 &= Var[X_i]^{-1} Cov[X_i, \bar{v}_{i\bullet} - \bar{Z}_{i\bullet} b_1] = -\pi b_1 \\ c_2 &= Var[X_i]^{-1} Cov[X_i, \bar{H}_{i\bullet} - \bar{Z}_{i\bullet} c_1] = -\pi c_1 \end{aligned} \tag{34}$$

To implement control for statistical and conceptual measurement error using the error correction parameters derived above, it is necessary to specify the error variance-covariance matrix Σ_{vv} and given this matrix, compute: Ω_{HH}. Since we are interested in evaluating the robustness of estimates to different values of the error matrix, we construct the error matrix as a function of the reliability of each SEL variable r_p and the correlation ρ_{pq} of measurement errors between errors p and q. The (p,q) element in the error matrix is given by:

$$\Sigma_{vv(p,q)} = r_p SD[Z_{ip}]\rho_{pq} r_q SD[Z_{iq}] \tag{35}$$

where the standard deviations of the SEL variables are based on the pooled sample. We consider different values of reliability and correlation in the robustness analysis, but as indicated above, for the primary results we set the reliability of each SEL variable to 85% and adopt the traditional assumption that measurement errors are uncorrelated across SEL variables and over time. Given the specified error variance-covariance matrix, equation (23) implies that the variance-covariance matrix of H_{it} is equal to:

$$\Omega_{HH} = T/(T-1)V_{DD} - \Sigma_{vv} \tag{36}$$

One useful implication of this formula is that it imposes constraints on the error matrix Σ_{vv}. Since Ω_{HH} is a variance matrix it must be positive semi-definite and the pairwise correlations must lie within the [-1,1] interval. Values of the error matrix that yield a Ω_{HH} matrix that violates these requirements are inadmissible.[14]

Alternative Models and Measurement Error Variances. The panel data model and estimation methods presented above facilitate estimation of several interesting models, including models to evaluate the robustness of the estimates. We consider the following model specifications, with implied measure error correction parameters.

1. No control for statistical and conceptual measurement error
2. Control for conceptual measurement error only: $\bar{H}_{i\bullet}$
3. Control for statistical measurement error only: v_{it} & $\bar{v}_{i\bullet}$
4. Full control for both sources of error
5. Robustness checks using different values of statistical error parameters
    a. Set Σ_{vv} and a_1, b_1, b_2, c_1, and c_2

The formulas for the four model specifications are listed in Table 7, where coefficients are indexed by model specification.

[14] As reported later in the robustness analyses, there are seemingly reasonable error matrix parameters that are inadmissible.

Table 7. Formulas for Coefficients by Model Specifications with Alternative Controls for Measurement Error

Model	**Stable Error**	**Statistical Error**	**Formula for Student Average or Stable Coefficient** κ	**Formula for Transitory Coefficient** λ
1	No	No	$\hat{\kappa}_1 = \hat{\kappa}_{bias}$	$\hat{\lambda}_1 = \lambda_{bias}$
2	Yes	No	$\hat{\kappa}_2 = [I - d_1]^{-1}\hat{\kappa}_{bias} - [I - d_1]^{-1} d_1 \hat{\lambda}_{bias}$	$\hat{\lambda}_2 = \lambda_{bias}$
3	No	Yes	$\hat{\kappa}_3 = [I - b_1]^{-1}\hat{\kappa}_{bias}$	$\hat{\lambda}_3 = [I - a_1]^{-1}\lambda_{bias}$
4	Yes	Yes	$\hat{\kappa}_4 = [I - b_1 - c_1]^{-1}\hat{\kappa}_{bias} - [I - b_1 - c_1]^{-1} c_1 [I - a_1]^{-1}\hat{\lambda}_{bias}$ $\hat{\kappa}_4 = \hat{\kappa}_2 = [I - d_1]^{-1}\hat{\kappa}_{bias} - [I - d_1]^{-1} d_1 \hat{\lambda}_{bias}$ $d_1 \equiv b_1 + c_1$	$\hat{\lambda}_4 = [I - a_1]^{-1}\lambda_{bias}$

One might presume that as additional controls for measurement error are implemented, the error correction parameters and associated error-corrected coefficient estimates change. That is only partly true. As indicated in Table 7, estimates of the transitory coefficient (λ) do not change as control for error in the student average is added; that is, from specifications #1 to #2 and #3 to #4. As indicated in Equation (30), the error correction multiplier a_1 depends only on the error matrix Σ_{vv} and the error correction multiplier $[I - a_1]^{-1}$.

Similarly, estimates of the coefficient on the student average/stable component (κ) do not change as control for statistical error is added; that is, from specifications #2 to #4. As indicated in the table the two formulas yield identical results. This result is perhaps unexpected, but it stems from the fact that it is not possible to distinguish between error due to $\bar{v}_{i\bullet}$ and $\bar{H}_{i\bullet}$ since both are unobserved and the former value is externally provided, thereby automatically determining the latter value. Consider the formula for the error corrected coefficient in Equation (29). The multiplier on the biased student average coefficient is the inverse of $[I - b_1 - c_1]$. Given Equations (32), (33), and (23), $d_1 = (b_1 + c_1)$ equals:

$$
\begin{aligned}
d_1 &= (b_1 + c_1) = V_{RR}^{-1}[\Sigma_{vv} + \Omega_{HH}]/T \\
&= V_{RR}^{-1} V_{DD}/(T-1)
\end{aligned}
\tag{37}
$$

Thus, this correction term does not depend on the error matrix Σ_{vv}; increases in Σ_{vv} are automatically offset by decreases in Ω_{HH}.[15] Furthermore, it can be shown that although the formulas for $\hat{\lambda}$ for specifications #2 and #4 differ, the error correction multipliers on $\hat{\lambda}_{bias}$ for $\hat{\kappa}_2$ and $\hat{\kappa}_4$ are equivalent; that is: $c_1[I - a_1]^{-1} = d_1$.

[15] In the special case where the model includes no time-invariant variables X_i, $V_{DD} = V_{RR}$ and the $(b_1 + c_1) = I/(T\text{-}1) = 0.5I$ in our application.

In summary, the model specification that corrects for conceptual error in measuring the stable SEL component and statistical measurement error of SEL (specification #4) essentially merges estimates from the two specifications that correct the two types of errors separately. As a result, we will focus in this paper primarily on estimates from the biased model (#1) and from the model that corrects for both sources of error (#4).

We can obtain approximate estimates of the standard errors for the alternative model specifications given that the alternative estimates are linear functions of the biased estimates. The matrix multipliers of the biased coefficients are given in Table 7. Note that the alternative estimates of λ are a function only of $\hat{\lambda}_{bias}$ whereas the alternative estimates of κ are function of both $\hat{\lambda}_{bias}$ and $\hat{\kappa}_{bias}$. Consider the latter case. Let $V_{\kappa\kappa}$ and $V_{\lambda\lambda}$ represent the error variance-covariance matrices for $\hat{\lambda}_{bias}$ and $\hat{\kappa}_{bias}$, respectively, and let M_1 and M_2 represent the matrix multipliers for the two biased estimates for a given model specification. Then, the estimate of the alternative estimate $\hat{\kappa}$ is given by:

$$\hat{\kappa} = M_1\kappa_{bias} + M_2\lambda_{bias} \tag{38}$$

and the error variance-covariance matrix for the alternative estimate $\hat{\kappa}$ is given by:

$$Var[\hat{\kappa}] = M_1 V_{\kappa\kappa} M_1' + M_2 V_{\lambda\lambda} M_2' \tag{39}$$

This estimator of the variance-covariance matrices is approximate because it ignores possible errors in the matrix multipliers, but errors in these matrices are likely quite small given the large size of our panel data set. In addition, we assess the robustness of the error corrected estimates to alternative values of Σ_{vv}.

The bottom line is that in order to correct for measurement error in the estimation of the CRE model it is necessary to control for two very different types of measurement, one type (conceptual error in student average variables) to obtain consistent estimates of the effects of stable predictors and a second type (statistical error) to obtain consistent estimates of the effects of transitory predictors. Given the latter result, the robustness analysis presented later in the paper need only to consider the effects of changes in the error matrix Σ_{vv} on the transitory coefficient estimates.

In the remainder of the methods section, we consider how to present estimates of the attendance and SEL panel data model in terms of the effects on both the transformed and raw (untransformed) attendance rates. We also define a composite SEL variable that, as demonstrated in the empirical section, efficiently characterizes the overall impact of SEL on student attendance.

Effects of SEL Based on the Model of the Transformed Student Attendance Rate

The building block of our analysis is the effect of a standardized change in each SEL variable and an SEL composite variable on the dependent variable, the transformed student attendance rate. These effects are simple to compute since the CRE model is linear in the predictors. We follow the standard practice of using the standard deviation of each SEL variable, transitory and student average, as the standardized change. As indicated in the table below, the appropriate standard deviations differ across the four different model specifications. The effect of a standardized change for SEL variable *p* is given by the product of the standardized change times the corresponding coefficient:

$$\begin{aligned} \Delta_{Tp} &= SD_{Tp}\hat{\lambda}_p \\ \Delta_{Sp} &= SD_{Sp}\hat{\kappa}_p \end{aligned} \tag{40}$$

where the subscripts *T* and *S* denote the transitory and student average (or stable) measures of SEL. We construct a composite SEL measure as the sum of the predictions of each SEL variable weighted by the estimated coefficient vectors. The standardized change in the predicted composite variable is given by square root of the variance of the predictions, given by:

$$\begin{aligned} \Delta_{T5} &= [\hat{\lambda}' V_{TT} \hat{\lambda}]^{0.5} \\ \Delta_{S5} &= [\hat{\kappa}' V_{SS} \hat{\kappa}]^{0.5} \end{aligned}$$

-

where, to simplify notation, we have identified the composite variable as *SEL* variable *p=5.*

V_{TT} and V_{SS} represent the variance-covariance matrices of the transitory and student average/stable predictors, which differ across the model specifications, as indicated in Table 8. Note that model specifications #1 and #2 do not correct for statistical error v_{it} and thus the sum of the variance matrices across the two columns equals the variance matrix for measured SEL (Z_{it}). Model specifications #3 and #4 correct for statistical measurement and, as a result, the sum of the variance matrices across the two columns equals the variance matrix for SEL corrected for statistical measurement error (Z_{it} - v_{it}). The two columns split up the variances of the two types of error into the between and within-student components, depending on the model specification.

Table 8. Variance-Covariance Matrices of Student Average/Stable and Transitory Variables by Model Specification and Degree of Control for Measurement Error

Model	**Stable Variable Control**	**Statistical Error Control**	**Variance of Student Average/Stable Variable**	**Variance of Transitory Variable**
1	No	No	$V_{MM} = \Omega_{FF} + (\Omega_{HH} + \Sigma_{vv})/T$	$V_{DD} = (\Omega_{HH} + \Sigma_{vv})(T-1)/T$
2	Yes	No	Ω_{FF}	$\Omega_{HH} + \Sigma_{vv}$
3	No	Yes	$\Omega_{FF} + \Omega_{HH}/T$	$\Omega_{HH}(T-1)/T$
4	Yes	Yes	Ω_{FF}	Ω_{HH}

Estimates of the effect size associated with the SEL variables are given by the standardized change variables presented above divided by the standard deviation of the dependent variable (the transformed student attendance rate), calculated using all three years of data in each cohort, given by ω_A.

Effects of SEL on Attendance Rate. We use estimates of the models of the transformed attendance rate considered above to estimate the effects of SEL measures on students with different expected attendance/chronic absenteeism levels. These calculations are motivated by the assumption that the model based on the transformed attendance rate adequately captures the true data generating process (DGP) of student attendance.[16,17] Since the model based on the transformed attendance rate implies a nonlinear relationship between SEL predictors and the raw attendance rate, the effects of SEL are non-linear, with effects lowest for students with high expected attendance and highest for students with expected low attendance. These non-linear effects can be directly computed using estimates of the linear CRE models. Note that the effect measures for the transformed and raw attendance variables are reported on different scales. As a result, the estimates are best compared using effect size estimates.

The CRE model based on the transformed attendance variable, $A_{it} \equiv \Phi^{-1}\left[R_{it}\right]$ from equation (5), can be written as:

$$A_{it} = \pi_{it} + e_{it} \tag{41}$$

where $\pi_{it} = \eta_t + (Z_{it} - \bar{Z}_{i\bullet})\lambda + \bar{Z}_{i\bullet}\kappa + X_i\beta + u_i$ equals the predicted values of A_{it} based on the transitory and student average SEL variables and coefficients (which vary across the different model specifications) and the student effect u_i but excluding the random error e_{it}. The standardized change effect measures considered above represent changes in the prediction variable π_{it}. An equation for the untransformed attendance rate is obtained by transforming both sides of equation (41) by the normal cumulative distribution function, which yields:

$$R_{it} = \Phi[A_{it}] = \Phi\left[\pi_{it} + e_{it}\right] \tag{42}$$

a nonlinear function of the predictors.

There are two standard methods for evaluating effects in nonlinear models: (1) evaluate the effects as the difference in predicted outcomes given the changes in the predictors and (2) evaluate the effects as the change in the predictors times the slope (derivative) of the predicted outcomes with respect to the change. We adopt the second approach for several reasons: it yields results that are like the first approach, it makes it transparent how the slope changes as a function of expected attendance, the computed effect is a linear function of the standardized effect change measures defined above, and (given the previous point) the standard errors are straightforward to compute.

---

[16] See Davidson and MacKinnon (1993, pp. 51-54) for discussion of DGPs.
[17] We have conducted some exploratory research to assess where the model based on the transformed attendance rate adequately captures the true DGP. We estimated models of attendance using an ordered probit model with multiple discrete levels. The estimated threshold parameters are consistent with our assumption that the normal inverse transformation fits the data well and inconsistent with the assumption that the raw (untransformed) attendance variable is the proper outcome variable.

Applying the second method, the effect of the standardized change effect on untransformed attendance is given approximately by:

$$\Delta(R)_{Tp(m)} = \frac{\partial R_{it}}{\partial A_{it}} \Delta_{Tp} = f_{R|A(m)} \Delta_{Tp}$$
$$\Delta(R)_{Sp(m)} = \frac{\partial R_{it}}{\partial A_{it}} \Delta_{Sp} = f_{R|A(m)} \Delta_{Sp} \quad (43)$$

where the derivative of *R* with respect to *A* is given by:

$$f_{R|A(m)} = \frac{\partial R_{it}}{\partial A_{it}} = \frac{\partial \Phi[A_{it}]}{\partial A_{it}} = \phi\left(\pi_m\right) \quad (44)$$

where $\phi(.)$ represents the standard normal density function and the derivative is evaluated at specified (and varying) values of predictions of transformed attendance, given by π_m for level *m*. The formula for the prediction π_m is provided below. The effect of the standardized change is calculating by multiplying the derivative f_{Rit} times he standardized change measures Δ_{Tp}, Δ_{Sp}, as indicated in equation (43). The denominator for the effect size is the standard deviation of the raw attendance variable, ω_R, calculated using all three years of data in each cohort.

It is informative to connect the effect size estimates for the transformed and raw (untransformed) attendance rates, since the latter varies across students. The effect size for the raw attendance rate equals the effect size for the transformed attendance rate times the following multiplier (which varies across students):

$$g_{R|A(m)} = (\omega_A / \omega_R) f_{R|A(m)} \quad (45)$$

This multiplier is reported in the empirical section of the paper (with different values for the pre- and post-pandemic period).

In summary, all SEL effects are driven by the model parameters and the standardized change effects Δ_{Tp}, Δ_{Sp} λ, κ (for a given model specification). The SEL effect on the raw attendance rate translates these fundamental effects (given the model assumptions) into policy-oriented effects with respect to the raw student attendance rate at different expected levels of predicted chronic absenteeism/attendance level *m*.

It is convenient to select different levels of the prediction π_m by specifying analytic quantiles of the distribution of π_{it}, rather than empirical quantile values. The latter approach requires estimation of the random effect u_i. We calculate π_m using the following steps.

1. Select quantile values Q_m for level *m*.
2. Calculate the associated normal deviate d_m, given the assumption that the distribution of predicted values π_{it} is normally distributed with standard deviation ω_π ; $d_m = \Phi^{-1}[Q_m]$.

3. Calculate the prediction[18]: $\pi_m = \pi_0 + d_m \omega_\pi$ where $\pi_0 = \Phi^{-1}[Mean(R)]$.

Effect size multipliers computed at selected quantile values are reported below in Table 16.

Empirical results are reported below for both the pre- and post-pandemic periods. All estimates are based on the pooled cohorts: grade cohorts 456, 567, and 678. We first report on the multivariate structure of the SEL variables. We next present estimates of the student attendance model based on the transformed student attendance rate for different model specifications and evaluate the robustness of the results. Subsequently we present effect estimates for three alternative policy-oriented interpretations of the estimates: effect size estimates based on the model of the transformed student attendance rate (A), effect size estimates on the raw attendance rate for students with different expected attendance/chronic absenteeism levels (R), and evaluation of the hypothesis that the change in social emotional learning explains the decline in student attendance from the pre-pandemic to the post-pandemic periods.

Empirical Results: The Multivariate Structure of SEL Variables

Table 9 reports the variances of the stable (F) and transitory (H) components and the intraclass correlation (ICC) coefficient for all variables: the transformed student attendance rate and the SEL measures for the pre-pandemic and post-pandemic periods.

Table 9. Variance Components for Pooled Samples: Pre- and Post-Pandemic Periods

Student Outcome	**Pre-Pandemic Period**			**Post-Pandemic Period**		
	Stable	Transitory	ICC	Stable	Transitory	ICC
Attendance rate transformed A	0.1070	0.0700	0.61	0.1450	0.0918	0.61
Self Efficacy	0.4072	0.4339	0.48	0.3994	0.4328	0.48
Self Management	0.5491	0.5276	0.51	0.4685	0.5681	0.45
Growth Mindset	0.4549	0.6084	0.42	0.4485	0.5666	0.44
Social Awareness	0.5997	0.7637	0.43	0.5237	0.8023	0.39

Table 9 indicates that the transformed attendance rate is moderately stable, with an intraclass correlation (ICC) equal to 60.45% and 61.23% in the pre- and post-pandemic samples, respectively. In contrast, the variances of the stable and transitory effects are comparable for all four SEL variables and less stable than the attendance variables. Tables 10a, 10b, and 10c expand the analysis to consider the multivariate structure of the SEL variables. Tables 10a and 10b report the correlations of the stable and transitory SEL components, respectively, for the pre- and post-pandemic periods. Table 10c reports correlations for the total measured SEL variables for these periods. Note that the multivariate variance components analysis is identical to the

[18] Given that the $R|A$ function is nonlinear and that values of R are greater than 0.5 (in fact, generally greater than 0.75), *Mean(R)* is lower than *Mean(A).* To accommodate this nonlinearity and properly center the different values of π_m we use $\pi_0 = \Phi^{-1}[\bar{R}]$ in place of *Mean(A)* in the formula.

univariate variance results reported in Table 9 but with the addition of correlations across SEL constructs.[19]

Table 10a. Correlation of Stable Variance Component for Pooled Samples: Pre- and Post-Pandemic Periods

	Stable Component: Pre-Pandemic Period					Stable Component: Post-Pandemic Period			
	SE	**SM**	**GM**	**SA**		**SE**	**SM**	**GM**	**SA**
SE	1.000	0.656	0.679	0.589		1.000	0.698	0.877	0.627
SM	0.656	1.000	0.542	0.732		0.698	1.000	0.709	0.762
GM	0.679	0.542	1.000	0.388		0.877	0.709	1.000	0.711
SA	0.589	0.732	0.388	1.000		0.627	0.762	0.711	1.000

Table 10b. Correlation of Transitory Variance Component for Pooled Samples: Pre- and Post-Pandemic Periods

	Transitory Component: Pre-Pandemic Period					Transitory Component: Post-Pandemic Period			
	SE	**SM**	**GM**	**SA**		**SE**	**SM**	**GM**	**SA**
SE	1.000	0.369	0.174	0.376		1.000	0.434	0.545	0.420
SM	0.369	1.000	0.100	0.430		0.434	1.000	0.440	0.437
GM	0.174	0.100	1.000	0.088		0.545	0.440	1.000	0.428
SA	0.376	0.430	0.088	1.000		0.420	0.437	0.428	1.000

Table 10c. Correlation of Total SEL Measures for Pooled Samples: Pre- and Post-Pandemic Periods

	Total SEL: Pre-Pandemic Period					Total SEL: Post-Pandemic Period			
	SE	**SM**	**GM**	**SA**		**SE**	**SM**	**GM**	**SA**
SE	1.000	0.512	0.402	0.474		1.000	0.556	0.697	0.509
SM	0.512	1.000	0.305	0.572		0.556	1.000	0.559	0.573
GM	0.402	0.305	1.000	0.217		0.697	0.559	1.000	0.546
SA	0.474	0.572	0.217	1.000		0.509	0.573	0.546	1.000

Table 9a indicates that the stable SEL components are highly correlated, with average correlations equal to 0.598 in the pre-pandemic period and 0.730 in the post-pandemic period. The correlations for the transitory components, reported in Table 9b, are also correlated, but less so: 0.326 and 0.467 in the pre- and post-pandemic periods, respectively. A major part of the reason that these correlations are lower on average in the pre-pandemic period is that growth mindset is much less correlated with the other three SEL constructs in this period, compared to the post-pandemic period. This is consistent with the findings of Bolt, Wang, Meyer & Pier (2020) and Wang, Pier, Meyer & Bolt (2019). The growth mindset survey items administered in the pre-pandemic period were designed to elicit rejection of a fixed mindset and thus tended to be negatively worded. Bolt et al (2020) showed that some students were confused by the wording

[19] The multivariate variance-covariance estimates (used to produce the correlations) will be used later in the paper for the model that controls for measurement error in the student average SEL measures.

of these items. The items administered in the post-pandemic period were converted to positively worded versions of the same items. Although the growth mindset items differed between the two periods, the two measures were included to provide complete information on the predictive power of the full set of SEL measures.

Given the fact that the SEL variables, particularly the stable components, are highly correlated, it is useful to consider how best to include these variables as model predictors. One approach, designed to limit multicollinearity, is to combine the measures into a composite variable using *a priori* weights. We do not pursue this approach because our review of psychology literature suggests that self-efficacy and self-management may have much stronger effects on student attendance than the other two SEL variables. Given the large size of the data used in our study, it is feasible to include the SEL variables separately without driving up standard errors due to multicollinearity.[20] However, for some of our analyses we construct a post-estimation composite variable that combines the SEL measures into a composite variable using the estimated coefficients as weights. One of the advantages of our approach is that we provide evidence on both the partial effects of SEL constructs but also, via the composite variable, evidence on the impact of SEL as an overall construct.

Empirical Results: Student Attendance and SEL Panel Data Model Estimates Based on the Transformed Attendance Variable

We first discuss the estimates based on the model with no correction for measurement error in student average SEL as a measure of the stable SEL component and no correction for statistical error. These estimates provide the foundation for all alternative model specifications, as explained above. Table 11 reports estimates of the effects of student average and transitory SEL components from the separate pre- and post-pandemic period models. Drawing from the psychology literature on risk factors that contribute to chronic absenteeism, we hypothesized that risk factors and SEL constructs such as self-efficacy and self-management measure the same personality traits or characteristics associated with determinants of student attendance and chronic absenteeism. We find strong support for this hypothesis: the effects of student average measures of self-efficacy and self-management are strong and highly significant predictors of student attendance. Measures of growth mindset and social awareness have less predictive power. A major finding is that the effects of self-efficacy and self-management (and the other two SEL measures) channel primarily through the student average measures of these variables, rather than through transitory changes in these variables. These results confirm the importance of using panel data models that provide information not just on the effects of changes in predictors but also the effects of student averages of these variables. The effects of the student average SEL variables are stronger in the post-pandemic period than in the pre-pandemic period. Indeed, the effect of self-efficacy increases by a factor of more than three in the post-pandemic period whereas the effect of self-management, the largest effect in the pre-pandemic period, increases by 20% in the post-pandemic period. Note that the estimated coefficients on the student averages of growth mindset and social awareness are relatively small, but negative and statistically

[20] Kanopka et al (2024) also present the results of models that include all SEL variables.

significant. We discuss that finding later based on the estimates that control for measurement error.

Table 11. CRE Estimates of the Models of Transformed Attendance Rate and SEL Variables: Pooled Samples, No Measurement Error Correction, Pre-and Post-Pandemic Periods

	Pre-Pandemic			**Post-Pandemic**		
Variable	**Coefficient**	**Std. Error**	**z-stat**	**Coefficient**	**Std. Error**	**z-stat**
Student Average SEL						
Self Efficacy	0.0311	0.0042	7.33	0.1126	0.0061	18.36
Self Management	0.0546	0.0039	13.99	0.0664	0.0049	13.46
Growth Mindset	-0.0061	0.0034	-1.83	-0.0389	0.0058	-6.73
Social Awareness	-0.0252	0.0033	-7.57	-0.0203	0.0042	-4.78
Transitory SEL						
Self Efficacy	0.0096	0.0021	4.57	0.0135	0.0027	4.99
Self Management	0.0026	0.0019	1.37	0.0056	0.0023	2.49
Growth Mindset	0.0051	0.0016	3.19	-0.0013	0.0024	-0.57
Social Awareness	0.0016	0.0016	1.01	0.0037	0.0019	1.99
Cohort and Year Effects	Yes	na	na	Yes	na	na
Demographic Variables	Yes	na	na	Yes	na	na
Random Effects	Yes	na	na	Yes	na	na
Measurement Error Correction	No	na	na	No	na	na
Student Effect Variance	0.0904	na	na	0.1290	na	na
Error Variance	0.0695	na	na	0.0917	na	na
Number of Students	23,191	na	na	22,897	na	na
Number of Observations	69,573	na	na	68,691	na	na

The other important result in Table 11 is that the variances of the student effect component, which captures time-invariant variables not included in the model, are large in both the pre- and post-pandemic models, much larger than contributions of the SEL variables and the demographic graphic variables included in the model, representing 51.2% of the variance in the transformed attendance variable in the pre-pandemic model and 54.4% in the post-pandemic model. In addition, the variances of the random year-specific error are also relatively large, representing 39.4% of the variance in the transformed attendance variable in the pre-pandemic model and 38.6% in the post-pandemic model. It is not unexpected that there are multiple unknown determinants of student attendance, both on average and from year-to-year, but that does not preclude the fact that the effects of SEL, particularly the student average component, are substantively important. We address that below by expressing the SEL effects in terms of their effect sizes.

Appendix Tables B.1 and B.2 present estimates of SEL coefficients for all four model specifications for the pre- and post-pandemic periods, respectively. We add two new statistics: the sum of the coefficients and the standard deviation of predicted attendance, reported separately for the student average/stable and transitory SEL components. These statistics provide an overall summary of the differences in predictive power of the two components in the alternative models. As indicated in the two tables, we can confirm the conclusion in the methods section that the model with full (double) measurement error correction (MEC) (specification #4) essentially merges estimates from the two specifications that correct the two types of errors separately (specifications #2 and #3). As a result, we will focus primarily on estimates from the biased model (#1) and from the model that corrects for both sources of error (#4).

Table 12 presents estimates of the biased model (#1) and the model with full control for measurement error (#4) for the pre- and post-pandemic periods. Two columns have been added to facilitate comparison of the estimates in each period: the ratio of the estimates with full measurement error correction to the biased estimates. In all but two cases the coefficients based on measurement error correction (MEC) are larger in absolute value than those that are not corrected for measurement error – see the ratios of the coefficients in the table.[21] The average coefficients for student average/stable SEL are larger due to MEC in the pre- and post-pandemic models by 8% and 30%, respectively. The standard deviations of the predictions are larger due to MEC in the pre- and post-pandemic models by 21% and 19%, respectively.[22]

The impact of MEC is even larger for the coefficients on the transitory SEL variables, with increases in the standard deviations of the predictions of 37% and 42% in the pre- and post-pandemic periods. Nonetheless, the coefficients and standard deviations of the predictions continue to be much higher for the coefficients on the student average/stable component relative to the coefficients on the transitory SEL component. Indeed, in the pre- and post-pandemic periods the ratios of the two standard deviations equal 5.4 and 7.3.

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[21] When measurement error control is applied to a single variable the error-corrected estimate is always larger than the biased estimate – the coefficient is corrected for attenuation. This is not the case if MEC is applied to multiple variables. This is especially true when the predictors are highly correlated, as in our application.

[22] Note that we might have expected even larger increases in the standard deviation due to correction for measurement error in student average SEL as a measure of the stable SEL component. However, the standard deviations of the predicted SEL effects are affected by both the change in the coefficients due to MEC (an increase in absolute value) and the change in the variance of the student average variable due to MEC (a decrease in the variance). As indicated in the table, the positive effect of measure error correction on the coefficients outweighs the reduction in the variance of the predictors. This result arises from the fact that we define a change in SEL as the standard deviation of these variables. Later in the paper we evaluate the degree to which changes in average SEL and the effects of SEL could account for the change over time in student attendance. In this case, the change in the coefficients due to MEC and the changes in average SEL are the two factors that matter. The changes in the standard deviations do not affect the results.

Table 12. Estimates of Attendance and SEL Models by Model Specification, Pooled Samples, Pre- and Post-Pandemic Periods

	Estimates by Model Specification and Pandemic Period									
	Pre-Pandemic Period					**Post-Pandemic Period**				
	1: Biased		**4: Full MEC**		**MEC/ Bias**	**1: Biased**		**4: Full MEC**		**MEC/ Bias**
SEL Variable	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Ratio**	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Ratio**
Student Average/ Stable SEL										
Self Efficacy	0.0311	*0.0042*	0.0488	*0.0084*	1.57	0.1214	*0.0092*	0.2070	*0.0149*	1.84
Self Management	0.0546	*0.0039*	0.0945	*0.0074*	1.73	0.0709	*0.0064*	0.1065	*0.0101*	1.60
Growth Mindset	-0.0061	*0.0034*	-0.0294	*0.0073*	4.80	-0.0421	*0.0089*	-0.1195	*0.0153*	3.07
Social Awareness	-0.0252	*0.0033*	-0.0550	*0.0063*	2.19	-0.0185	*0.0054*	-0.0386	*0.0093*	1.90
Sum of Coefficients	0.0544	na	0.0588	na	1.08	0.1318	na	0.1555	na	1.30
SD of Prediction	0.0480	na	0.0579	na	1.21	0.0908	na	0.1083	na	1.19
Transitory SEL										
Self Efficacy	0.0096	0.0021	0.0142	0.0037	1.49	0.0266	*0.0064*	0.0266	*0.0064*	1.98
Self Management	0.0026	0.0019	0.0022	0.0038	0.85	0.0068	*0.0042*	0.0068	*0.0042*	1.21
Growth Mindset	0.0051	0.0016	0.0062	0.0022	1.21	-0.0110	*0.0054*	-0.0110	*0.0054*	8.19
Social Awareness	0.0016	0.0016	0.0005	0.0029	0.31	0.0036	*0.0032*	0.0036	*0.0032*	0.97
Sum of Coefficients	0.0189	na	0.0231	na	1.22	0.0260	na	0.0260	na	1.21
SD of Prediction	0.0078	na	0.0107	na	1.37	0.0104	na	0.0148	na	1.42

One possible reason for the relatively small estimates of the transitory SEL effects is that the error values selected to control for statistical error are incorrect. We evaluate the robustness of transitory effects by computing the standard deviation of predictions given different measurement error values. As discussed in the methods section, we vary both the reliability of the SEL variables and the correlation in errors across the four SEL variables. It is unusual to allow for correlated measurement error (since it cannot typically be measured unless true values are observed), but it is feasible to do so when implementing measurement error correction. As indicated in Table 13, different values of reliability and error correlation have minimal effects on the predictive power of transitory SEL.[23] The value of the standard deviation of predictions is only slightly higher at its maximum value, 0.0183, compared to a value of 0.0148 in our preferred model. Given the above findings, we focus primarily on the effects due to the average student and stable SEL component in the remainder of the paper.

Table 13. Robustness of Transitory Effects Given Alternative Statistical Error Values

	Standard Deviation of Prediction Given Transitory Effects				
	Reliability				
Error Correlation	1	0.9	0.85	0.80	0.75
0	0.0128	0.0138	0.0148	0.0171	x
0.2	na	0.0140	0.0148	0.0160	0.0183
0.4	na	0.0141	x	0.0161	0.0176

Note: x denotes an inadmissible value

One of the unexpected results in Table 12 (and in Appendix Tables B.1 and B.2) is that whereas the effects of student average and stable self-efficacy and self-management are positive and large, the effects of growth mindset and social awareness are negative, although generally smaller than the effects of self-efficacy and self-management (except in the case of growth mindset with MEC in the post-pandemic period). Since these results are statistically significant, we cannot attribute the results to imprecision due to multicollinearity. Since we do not think that growth mindset and social awareness have genuine negative effects on student attendance, we conjecture that the negative coefficients arise because self-efficacy and self-management, as measured given the survey questions listed in Appendix A, measure aspects of growth mindset and social awareness, as well as the true self-efficacy and self-management constructs. This hypothesis is consistent with the factor analyses reported in Wang et al (2019) and with the fact that four measured SEL variables are highly correlated (see Table 10).

A simple factor model demonstrates the plausibility of this conjecture. Suppose that the effects of true, hypothetical measures of stable SE and SM equal 0.2070 and 0.1065, the coefficients in Table 14 from the MEC model in the post-pandemic period. In contrast, suppose that the corresponding coefficients on GM, and SA are not negative but equal zero. Suppose, as stated above, the observed survey-based measures of these constructs are given by:

$$\begin{aligned} Z_1 &= 1.0SE(1.0) + GM(0.5) \\ Z_2 &= SM(1.0) + SA(0.5) \\ Z_3 &= GM(1.0) \\ Z_4 &= SA(1.0) \end{aligned} \tag{46}$$

It can be shown that the coefficients on the observed stable SEL measures are given as reported in Table 13.

[23] Note that for some values of the SEL error distribution estimates of the model are inadmissible because they imply correlations of the transitory SEL components that are out of range.

Table 14. Actual and Hypothetical Estimates of the Effects of Stable SEL Components with Measurement Correction in the Post-Pandemic Period

	Post-Pandemic Period	
	Coefficients	
SEL Variable	**Actual MEC Coefficients**	**Hypothetical Coefficients**
Stable Component		
Self Efficacy	0.2070	0.2070
Self Management	0.1065	0.1065
Growth Mindset	-0.1195	-0.1035
Social Awareness	-0.0386	-0.0535

The hypothetical coefficients are very close to the actual coefficients, which supports the conjecture that the negative coefficients on growth mindset and social awareness are plausibly due to the measurement structure of the four SEL constructs. One of the implications of the above analyses is that while it is informative to consider the partial effects of each SEL variable (student average/stable and transitory components) it is also useful to consider the effects of the composite variables that combine all four SEL measures. Given that the coefficients on the self-efficacy and self-management variables are collectively larger than the effects of growth mindset and social awareness, we view the composite variables as measures that largely represent self-efficacy and self-management.

Empirical Results: Effect Sizes of Student Attendance and SEL Panel Data Model Estimates Based on the Transformed Attendance Variable

To better understand the policy-relevant importance of SEL with respect to student attendance, we next consider estimates in terms of their effect sizes; that is, effects relative to the standard deviation of attendance (defined in terms of the transformed or raw attendance rate, depending on the table). The required standard deviations for the models based on the transformed attendance variable are reported in Appendix Table B.3. As indicated in the table, the standard deviation of the transformed and raw attendance variables increased in the post-pandemic period and as previously discussed, the means of these variables declined substantially between periods. Even though average SEL declined over the two periods, as reported in Table 5 and Figure 3, the standard deviations of the SEL variables stayed roughly constant over time. Note that the standard deviations of the measurement error corrected components differ from those not corrected for error. The standard deviations of the student stable components are lower due to removal of the variance in the average transitory components. In contrast, the standard deviations of the transitory components are higher due to recovery of this source of variance but lower due to removal of statistical error. The net difference is an increase in the variance of the transitory components.

Effect size estimates are reported in Table 15 for the model with np correction for measurement error (#1) and full correction for error (#4). Consistent with the parameter estimates discussed above, the effect sizes of the student average and stable SEL component effects are much larger than those for the transitory components, even after the upward adjustment to the variance of the transitory components. As a result, in the remainder of this paper we concentrate on the estimates of the student average and stable SEL component effects.

Effect size estimates of the student average SEL measures (not corrected for measurement error) are quite large. The self-efficacy effect size estimates equal 0.0552 and 0.1706 in the pre- and post-pandemic period, respectively. The corresponding effects based on the stable SEL component (corrected for measurement error) are even larger, 0.0745 and 0.2686, respectively. The self-management effect size estimates are also quite large and roughly comparable in the pre- and post-pandemic periods. The effect sizes for self-management, not corrected for measurement error, equal 0.111 in both periods and range from 0.15 to 0.17 in the two periods when corrected for measurement error.

Table 15. The Effect Size of SEL Measures and a Composite SEL Measure by Model Specification, Pooled Sample, Pre- and Post-Pandemic Periods

Effect Size	**Self Efficacy**	**Self Management**	**Growth Mindset**	**Social Awareness**	**SEL Composite**
Pre-Pandemic Period					
Effect Size					
Student Average (No MEC, Model #1)	0.0552	0.1110	-0.0119	-0.0556	0.1143
Student Stable Component (with MEC, Model #4)	0.0745	0.1674	-0.0471	-0.1020	0.1378
Transitory Component (No MEC, Model #1)	0.0123	0.0037	0.0077	0.0027	0.0186
Transitory Component (with MEC, Model #4)	0.0187	0.0032	0.0100	0.0009	0.0255
Post-Pandemic Period					
Effect Size					
Student Average (No MEC, Model #1)	0.1706	0.1106	-0.0640	-0.0373	0.1865
Student Stable Component (with MEC, Model #4)	0.2686	0.1496	-0.1646	-0.0578	0.2225
Transitory Component (No MEC, Model #1)	0.0149	0.0071	-0.0016	0.0056	0.0214
Transitory Component (with MEC, Model #4)	0.0304	0.0090	-0.0146	0.0058	0.0304

As in the previous tables, the effect sizes for growth mindset and social awareness are negative. If we accept the conjecture stated previously in the paper that these negative results are due to the measurement structure of the four SEL constructs, the estimated effect sizes for the SEL composite variables may be as, or more, policy relevant than the separate estimates for self-efficacy and self-management. The effect sizes for the composite SEL variable (not corrected for measurement error) are quite large, 0.1143 and 0.1865 in the pre- and post-pandemic periods and 0.1378 and 0.2225 in the two periods (corrected for measurement error).

Empirical Results: Effect Size Estimates of SEL on Raw Attendance Rate by Quantile Level of Predicted Attendance.

One of the interesting and policy relevant features of our model of student attendance is that the model implies a nonlinear relationship between SEL predictors and the raw attendance rate and, as a result, the effects of SEL are non-linear, with effects lowest for students with high expected attendance and highest for students with expected low attendance. We assume that the model based on the transformed attendance rate adequately captures the true data generating process (DGP) of student attendance.[24, 25] In this section we use estimates of the model of the transformed attendance rate presented above to estimate the effects of SEL measures on students with different expected attendance/chronic absenteeism levels. These non-linear effects can be directly computed using estimates of the linear CRE model. Since the effect measures for the transformed and raw attendance variables are reported on different scales, the estimates are best compared using effect size estimates.

As discussed above, we evaluate the nonlinear effects of SEL as the change in the predictors reported in Table 12 times the slope (derivative) of predicted raw attendance with respect to the change. Equations (43) to (45) define the multipliers used to calculate effect size estimates as a function of different levels of predicted attendance, ranging from quantiles 5% to 99%. Table 16 reports these multipliers for the pre- and post-pandemic models. Given the nonlinearity embedded in the model the multiplier is higher than one for students with below average expected attendance and lower than one for students with above average expected attendance. The multipliers are somewhat higher for the post-pandemic estimates compared to the pre-pandemic estimates. This is due to the relatively lower attendance rates in the post-pandemic period, thereby creating more space for increases in attendance in response to increases in SEL.

[24] See Davidson and MacKinnon (1993, pp. 51-54) for discussion of DGPs.

[25] We have conducted some exploratory research to assess where the model based on the transformed attendance rate adequately captures the true DGP. We estimated models of attendance using an ordered probit model with multiple discrete levels. The estimated threshold parameters are consistent with our assumption that the normal inverse transformation fits the data well and inconsistent with the assumption that the raw (untransformed) attendance variable is the proper outcome variable.

Table 16. Effect Size Weights for Effect on Raw Attendance Rate: Pre- and Post-Pandemic Periods

		Pre-Pandemic Period		**Post-Pandemic Period**	
Attendance Quantile Level	**Level deviate *d(m)***	**Predicted Attendance** $\pi(m)$	**Effect Size Weight R|A**	**Predicted Attendance** $\pi(m)$	**Effect Size Weight R|A**
5%	-1.645	1.422	1.966	0.903	2.084
10%	-1.282	1.541	1.649	1.042	1.821
25%	-0.674	1.739	1.191	1.273	1.393
50%	0.000	1.960	0.792	1.530	0.972
75%	0.674	2.181	0.502	1.787	0.635
90%	1.282	2.379	0.319	2.018	0.409
99%	2.326	2.721	0.133	2.416	0.169
Average *R*		0.975		0.937	
Average π_0		1.960		1.530	
SD: ω_π		0.327		0.381	

Effect size estimates of student average SEL on the raw attendance rate by quantile level are reported in Tables 17a and 17b based on the effect size estimates on the transformed attendance rate reported in Table 15 and the multipliers given in Table 16. The effect size estimates for the transformed attendance rate are repeated in the table. To simplify the presentation, effect estimates are based on estimates of the model with full measurement error correction and only for the effects of student average SEL.

As expected, due to the nonlinear structure of the attendance model, the effect size estimates are much higher for students with predicted attendance levels less than the middle of the distribution. For students at the 10% quantile, the self-efficacy effect sizes equal 0.123 and 0.489 in the pre- and post-pandemic periods, respectively. The corresponding effect sizes estimates for self-management equal 0.276 and 0.272. Self-management is the stronger predictor in the pre-pandemic period and self-efficacy is the stronger predictor in the post-pandemic period. For high levels of predicted attendance, the effect sizes of all predictors are much smaller. The effect sizes for students at the 90% quantile equal 0.024 and 0.0.110 for self-efficacy in the pre- and post-pandemic periods, respectively.

As above, the effect size estimates for growth mindset and social awareness are negative at all predicted attendance quantiles. If we accept the conjecture stated previously in the paper that these negative results are due to the measurement structure of the four SEL constructs, the estimated effect sizes for the SEL composite variables may be as, or more, policy relevant than the separate estimates for self-efficacy and self-management. As in the case of the separate estimates for these two constructs, the effect sizes for the SEL composite variables are much higher for students with predicted attendance levels less than the 50% quantile, especially in the post-pandemic period. For students at the 10% quantile, the SEL composite effect sizes equal 0.227 and 0.405 in the pre- and post-pandemic periods, respectively.

Table 17a. Effect Size Estimates of Student Average SEL on Transformed Attendance and Raw Attendance Rate by Quantile Level, Pooled Samples, Full Measurement Error Correction: Pre-Pandemic Period

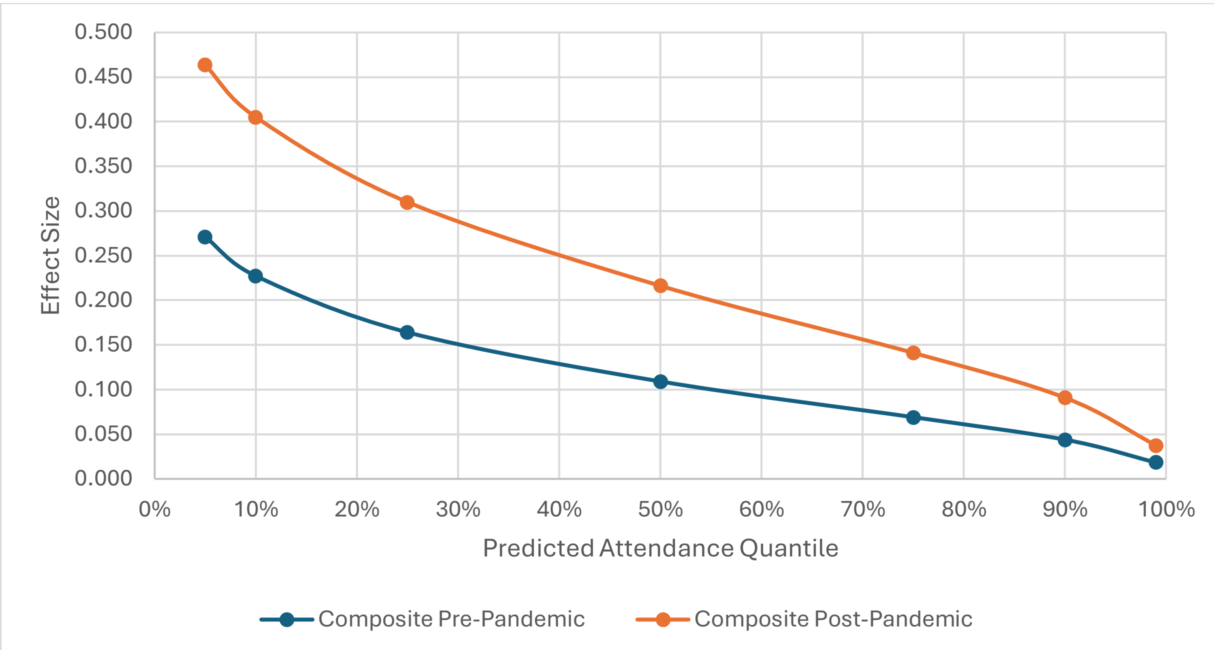
	Pre-Pandemic Period				
Effect Size	**Self Efficacy**	**Self Management**	**Growth Mindset**	**Social Awareness**	**SEL Composite**
Transformed Attendance	0.074	0.167	-0.047	-0.102	0.138
Raw Attendance Rate by Quantile					
5%	0.146	0.329	-0.093	-0.201	0.271
10%	0.123	0.276	-0.078	-0.168	0.227
25%	0.089	0.199	-0.056	-0.121	0.164
50%	0.059	0.133	-0.037	-0.081	0.109
75%	0.037	0.084	-0.024	-0.051	0.069
90%	0.024	0.053	-0.015	-0.033	0.044
99%	0.010	0.022	-0.006	-0.014	0.018

Table 17b. Effect Size Estimates of Student Average SEL on Transformed Attendance and Raw Attendance Rate by Quantile Level, Pooled Samples, Full Measurement Error Correction: Post-Pandemic Period

	Post-Pandemic Period				
Effect Size	**Self Efficacy**	**Self Management**	**Growth Mindset**	**Social Awareness**	**SEL Composite**
Transformed Attendance	0.269	0.150	-0.165	-0.058	0.222
Raw Attendance Rate by Quantile					
5%	0.560	0.312	-0.343	-0.120	0.464
10%	0.489	0.272	-0.300	-0.105	0.405
25%	0.374	0.208	-0.229	-0.081	0.310
50%	0.261	0.145	-0.160	-0.056	0.216
75%	0.171	0.095	-0.105	-0.037	0.141
90%	0.110	0.061	-0.067	-0.024	0.091
99%	0.045	0.025	-0.028	-0.010	0.038

Effect size estimates for the SEL composite are presented graphically in Figure 4. As indicated in the figure, effect size estimates exceed 0.10 for students with predicted attendance less than or equal to the 50% quantile in the pre-pandemic period. The effects are even larger in the post-pandemic period. In this period, effect size estimates exceed 0.10 for students with predicted attendance less than or equal to the 75% quantile.

Figure 4. Effect Size Estimates of SEL Composite on Raw Attendance Rate by Quantile Level, Full Model Measurement Error Correction: Pre- and Post-Pandemic Periods



Given the possibility that the measured SEL variables are correlated with causes of attendance not included in the model and the estimates are based on a quasi-experimental model, we treat the effects reported in this paper as upper bound estimates of the causal effect of SEL on student attendance Nonetheless, the estimated effects are very strong and are important from the policy, evaluation, and measurement perspectives, as discussed below.

Empirical Results: Are the Changes in Social Emotional Learning Large Enough to Explain the Decline in Student Attendance?

We next consider whether the SEL effects estimated in this paper are sufficiently large to explain the very large change in student attendance between the pre- and post-pandemic periods. Table 18 sets the baseline for evaluating the decline in student attendance between these periods. The table reports average attendance and the change in average attendance between the pre- and post-pandemic periods based on the transformed and raw attendance scales. Average attendance on the raw scale declined by scale declined from 0.975 to 0.937, an effect size decline of 123% given that the standard deviation of raw attendance equaled 0.031 in the pre-pandemic period. The corresponding decline in average attendance measured on the transformed scale was equally large, 100%. These are, of course, enormous changes.

Table 18. Change in Average Student Attendance: Transformed Attendance Scale and Attendance Rate, Pooled Sample

	Transformed Attendance Scale		**Attendance Rate**
Pre-Pandemic Period	2.120		0.975
Post-Pandemic Period	1.699		0.937
Change in Average Attendance	-0.421		-0.0381
Attendance SD in Pre-Pandemic Period	0.420		0.031
Effect Size of Change in Average Attendance	-100%		-1.23%

In Table 19 we evaluate the effects of changes in SEL on attendance using estimates based on the transformed attendance scale and all three years in the pre- and post-pandemic data sets. Thus, the results are based on the student average or stable measures of SEL. Results are presented from the model that does not control for measurement error (#1) and from the model that controls for measurement error (models #2 and #4, which yield identical results). Panel A documents the change in each of the four SEL measures. Consistent with the findings in Table 4 and Figure 1, the reported changes in all four SEL constructs were large, on the order of 25% of a standard deviation of these measures (the combined stable and transitory components – see Table 9). Panels B and C report the effects of SEL change on transformed attendance based on estimates from the models that do and do not correct for measurement error in student average SEL as a measure of the stable SEL component, respectively. Changes in the effects of SEL over time are based on the coefficients on student average or stable SEL components since the average effects of transitory components are zero by construction. Following the Blinder-Oaxaca decomposition, changes in the effects of SEL on attendance consist of two parts: the part due to the change in average SEL and the part due to the change in SEL coefficients (Blinder, 1973; Oaxaca, 1973). Table 19 reports these two changes and their sum. The total sum is also evaluated in terms of the change due to SEL as a proportion of the change in average transformed attendance and the effect size of the change, the change divided by the standard deviation of transformed attendance. We report the change effects for all four SEL variables but focus on the total change estimates in the far-right column since, as argued above, the total change (or change in the composite measure) combines both the strong positive effects of self-efficacy and self-management and the negative effects of growth mindset and social awareness.[26] Since the attendance model is additive in the SEL variables, the predicted change in attendance due to all four SEL variables is simply the sum of the four effects.

As indicated in Table 19, in the model without measurement error correction (Panel B) the proportional change and the effect size due to SEL equal 5.5% in the pre-pandemic period.[27] In

[26] We also caution against over-interpreting the results for growth mindset (and the other SEL constructs, too) since the growth mindset survey items were changed from a negative to a positive orientation from the pre- to the post-pandemic periods. We trust the results for the total change in SEL over time more than the separate construct results.
[27] These two statistics are not, in general, equal. They happen to be equal in our application because, as reported in Table 16, the change in average attendance and the standard deviation in attendance in the pre-pandemic period are identical.

the model with measurement error correction, the SEL coefficients are larger (Panel C) and the proportional change and effect size due to SEL is approximately double that of the model that does not correct for measurement error, 10.5%.

The bottom line is that although the effect sizes of SEL in both the pre- and post-pandemic periods are relatively large, especially for students with low predicted attendance, they explain only a small percentage of the decline over time in student attendance. Although we caution against interpreting the results from our quasi-experimental model of student attendance as fully causal, the fact that changes in SEL over time could account for 5 to 10 percent of the decline is plausible. Moreover, our results establish the predictive validity of SEL measures with respect to student attendance, although that predictive power resides primarily in the student average or stable measures of SEL.

Table 19. The Effect of Changes over Time in Average SEL Measures on Transformed Attendance Scale, With and Without Full Measurement Error Correction, Pooled Sample

Statistic	**Self Efficacy**	**Self Management**	**Growth Mindset**	**Social Awareness**	**Total Change**
Panel A. Average SEL					
Pre-Pandemic Average	-0.010	0.035	-0.014	0.120	
Post-Pandemic Average	-0.247	-0.234	-0.414	-0.138	
Change in Average	-0.237	-0.268	-0.400	-0.258	
Panel B. Effects of SEL Change Based on Model without Measurement Error Correction					
Effects of Change in SEL and SEL Coefficients					
Change due to Change in SEL	-0.0074	-0.0146	0.0024	0.0065	-0.0131
Change due to Change in SEL Coefficients	-0.0201	-0.0028	0.0136	-0.0007	-0.0100
Total Change over time Due to SEL	-0.0275	-0.0174	0.0160	0.0058	-0.0231
Total Change over Time as a Proportion of the Change in Attendance	6.5%	4.1%	-3.8%	-1.4%	5.5%
Effect Size of Total Change	-0.0654	-0.0415	0.0381	0.0138	-0.0549
Panel C. Effects of SEL Change Based on Model with Full Measurement Error Correction					
Effects of Change in SEL and SEL Coefficients					
Change due to Change in SEL	-0.0116	-0.0254	0.0118	0.0142	-0.0110
Change due to Change in SEL Coefficients	-0.0390	0.0066	0.0039	-0.0048	-0.0333
Total Change over time Due to SEL	-0.0506	-0.0188	0.0157	0.0094	-0.0443
Total Change over Time as a Proportion of the Change in Attendance	12.0%	4.5%	-3.7%	-2.2%	10.5%
Effect Size of Total Change	-0.1205	-0.0448	0.0373	0.0224	-0.1056

Summary and Conclusions

This study investigates the relationship between social-emotional learning (SEL) and student attendance, including chronic absenteeism, using a large longitudinal dataset. The SEL constructs examined are self-efficacy, self-management, growth mindset, and social awareness. The research introduces new panel data models that aim to better capture the true relationship between SEL and attendance outcomes.

The model developed in this study incorporates three key features. First, it distinguishes between stable (student average) and transitory (year-to-year) effects of SEL, emphasizing that most policy studies overlook the stable component. We argue that causal effects can stem from stable traits, not just change over time. Second, the model accounts for nonlinearity in the relationship between SEL and attendance, showing that SEL has a stronger impact on students with lower expected attendance. Third, the model adjusts for measurement error in SEL variables, both in terms of general unreliability and inaccuracy in estimating the stable SEL trait.

The findings show that self-efficacy and self-management are strong positive predictors of attendance and are associated with lower chronic absenteeism. In contrast, growth mindset and social awareness have smaller but statistically significant negative coefficients. We suggest these negative results are likely due to measurement overlap, where the survey items for self-efficacy and self-management also capture aspects of the other two constructs. A composite SEL measure was created to optimally combine the four constructs. Given that the coefficients on self-efficacy and self-management variables are collectively larger than the effects of growth mindset and social awareness, we view the composite SEL variable as a measure that largely represents self-efficacy and self-management. Our results are also consistent with the view that a general SEL factor is the essential predictor of student attendance. Bolt, Wang, and Meyer (2025), in their multi-level bifactor model of SEL provide support for the existence of a strong general SEL factor.

Importantly, the study finds that the predictive power of SEL lies primarily in the long-term (stable) measures rather than short-term (transitory) changes. These effects are significantly stronger in the post-pandemic period, with effect sizes for the average student increasing from 0.1378 to 0.2225. For students with low predicted attendance (at the 10th percentile), the effect sizes are even larger—0.227 before the pandemic and 0.405 after.

Although we caution against interpreting the results from our quasi-experimental model of student attendance as fully causal, the fact that changes in SEL over time could account for 5 to 10 percent of the decline is plausible. Moreover, our results establish the predictive validity of SEL measures with respect to student attendance, although that predictive power resides primarily in the student average or stable measures of SEL.

From a policy perspective, the results validate the use of SEL surveys for identifying students at risk of poor attendance. Average SEL scores, particularly in self-efficacy and self-management, are useful for predictive analytics and early warning systems. The study suggests that interventions should focus on improving these stable SEL traits, especially for students with low expected attendance. Future evaluations should measure the impact of interventions on long-term SEL outcomes rather than short-term fluctuations.

The statistical/econometric contributions of the project are potentially important and applicable to other research applications. Our measure of student attendance addresses the fact that the distribution of annual student attendance rates is highly left-skewed. We transform the attendance rate using the inverse probit function. One of the major advantages of this approach is that the model fits within the class of generalized linear models (GLM) and thus the right hand-side of the model is a linear regression with random student effects.

We begin model development of the right-hand side of the model using a standard evaluation method, the fixed effects (FE) (within variance) model. A limitation of this approach is that it yields estimates of predictors solely based on changes (or transitory within variation) in predictors. We instead adopt the correlated random effects (CRE) model (Mundlak, 1978; Wooldridge, 2010) which yields estimates of within-variance parameters that are identical to those of the FE model but also provides estimates of the effects of student average variables. We consider a hypothetical factor analysis model of the SEL constructs that demonstrates that the coefficients on the student average variables potentially contain valid information on the causal effects of predictors. We thus adopt the CRE model as our maintained model and report estimates of the effects of both the transitory and student average (stable) predictors. We treat the effects estimates reported in this study as upper bound estimates of the causal effect of SEL on student attendance given the possibility that these variables are correlated with causes of attendance not included in the model and the estimates are based on a quasi-experimental model. The value of this expanded approach is that we can report estimates of both the effects of transitory and stable (student average) components unlike traditional approaches which report only the former. Our model estimates indicate that the effects of the stable and student average components dwarf the estimates of the transitory component.

We develop a model that accounts for two types of error in SEL variables: error due to unreliability in the measured variables (statistical error) and error in student average SEL as a measure of the stable component of SEL (conceptual error). We show that correcting for both types of measurement error yields increased estimates of the effects of the transitory and stable SEL components, and the estimates are robust to alternative assumptions about the structure of measurement error. Perhaps surprisingly, correction for statistical error primarily affects estimates of the effects of transitory SEL whereas correction for conceptual error solely affects estimates of the effects of the stable SEL component. This stems from the fact that it is not possible to distinguish between statistical and conceptual error since only the sum of the two components is known. Imposing the externally provided variance of statistical error automatically determines the value of conceptual error.

We recommend further quasi-experimental research to confirm the robustness of these findings, particularly with respect to the nonlinear specification of the model to address skewness in the attendance rate. We have conducted some exploratory research to assess where the model based on the transformed attendance rate adequately captures the true DGP. We estimated models of attendance using an ordered probit model with multiple discrete levels. The estimated threshold parameters are consistent with our assumption that the normal inverse transformation fits the data well and inconsistent with the assumption that the raw (untransformed) attendance variable is the proper outcome variable. Liu and Loeb (2021) consider another approach to modeling attendance rates using the negative binomial regression model.

We recommend building on the methods used in this paper to consider other student outcomes such as student achievement and other measures of SEL.

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Appendix A. Core Districts' Student Social-Emotional Learning Survey Items

Self-Efficacy

How confident are you about the following at school?

1. I can earn an A in my classes.
2. I can do well on all my tests, even when they're difficult.
3. I can master the hardest topics in my classes.
4. I can meet all the learning goals my teachers set.

(Not at All Confident, A Little Confident, Somewhat Confident, Mostly Confident, Completely Confident)

Self-Management

First, we'd like to learn more about your behavior, experiences, and attitudes related to school. Please answer how often you did the following during the past 30 days. During the past 30 days…

1. I came to class prepared.
2. I remembered and followed directions.
3. I got my work done right away instead of waiting until the last minute.
4. I paid attention, even when there were distractions.
5. I stayed calm even when others bothered or criticized me.

(Almost Never, Once in a While, Sometimes, Often, Almost All the Time)

Growth Mindset: Negative (Fixed Mindset) Survey Items

In this section, please think about your learning in general.
Please indicate how true each of the following statements is for you:

1. My intelligence is something that I can't change very much.
2. Challenging myself won't make me any smarter.
3. There are some things I am not capable of learning.
4. If I am not naturally smart in a subject, I will never do well in it.

(Not At All True, A Little True, Somewhat True, Mostly True, Completely True)

Growth Mindset: Positive Survey Items

In this section, please think about your learning in general.
Please indicate how true each of the following statements is for you:

1. I can change my intelligence with hard work.
2. I can increase my intelligence by challenging myself.
3. I am capable of learning anything.
4. I can do well in a subject even if I am not naturally good at it.

(Not at All True, A Little True, Somewhat True, Mostly True, Completely True)

Social Awareness

In this section, please help us better understand your thoughts and actions when you are with other people.

Please answer how often you did the following during the past 30 days. During the past 30 days…

1. How carefully did you listen to other people's points of view?

(Not Carefully at All, Slightly Carefully, Somewhat Carefully, Quite Carefully, Extremely Carefully)

2. How often did you compliment others' accomplishments?

(Almost Never, Once in a While, Sometimes, Often, Almost All the Time)

3. How well did you get along with students who are different from you?

(Did Not Get Along at All, Got Along a Little Bit, Got Along Somewhat, Got Along Pretty Well, Got Along Extremely Well)

4. How clearly were you able to describe your feelings?

(Not at All Clearly, Slightly Clearly, Somewhat Clearly, Quite Clearly, Extremely Clearly)

5. When others disagreed with you, how respectful were you of their views?

(Not at All Respectful, Slightly Respectful, Somewhat Respectful, Quite Respectful, Extremely Respectful)

Appendix Table B.1. Estimates of Attendance and SEL Models, Pooled Samples: Pre-Pandemic Period

	Estimates by Model Specification							
	1: Biased		**2: Stable MEC**		**3: Stat MEC**		**4: Full MEC**	
SEL Variable	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***
Student Average/ Stable SEL								
Self Efficacy	0.0311	*0.0042*	0.0488	*0.0084*	0.0353	*0.0053*	0.0488	*0.0084*
Self Management	0.0546	*0.0039*	0.0945	*0.0074*	0.0678	*0.0050*	0.0945	*0.0074*
Growth Mindset	-0.0061	*0.0034*	-0.0294	*0.0073*	-0.0105	*0.0040*	-0.0294	*0.0073*
Social Awareness	-0.0252	*0.0033*	-0.0550	*0.0063*	-0.0366	*0.0042*	-0.0550	*0.0063*
Sum of Coefficients	0.0544	na	0.0588	na	0.0560	na	0.0588	na
SD of Prediction	0.0480	na	0.0579	na	0.0516	na	0.0579	na
Transitory SEL								
Self Efficacy	0.0096	0.0021	0.0096	*0.0021*	0.0142	0.0037	0.0142	0.0037
Self Management	0.0026	0.0019	0.0026	*0.0019*	0.0022	0.0038	0.0022	0.0038
Growth Mindset	0.0051	0.0016	0.0051	*0.0016*	0.0062	0.0022	0.0062	0.0022
Social Awareness	0.0016	0.0016	0.0016	*0.0016*	0.0005	0.0029	0.0005	0.0029
Sum of Coefficients	0.0189	na	0.0189	na	0.0231	na	0.0231	na
SD of Prediction	0.0078	na	0.0095	na	0.0087	na	0.0107	na

Appendix Table B.2. Estimates of Attendance and SEL Models, Pooled Samples: Post-Pandemic Period

	Estimates by Model Specification							
	1: Biased		**2: Stable MEC**		**3: Stat MEC**		**4: Full MEC**	
SEL Variable	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***	**Coeff.**	***Std. Error***
Student Average/ Stable SEL								
Self Efficacy	0.1126	*0.0061*	0.2070	*0.0149*	0.1214	*0.0092*	0.2070	*0.0149*
Self Management	0.0664	*0.0049*	0.1065	*0.0101*	0.0709	*0.0064*	0.1065	*0.0101*
Growth Mindset	-0.0389	*0.0058*	-0.1195	*0.0153*	-0.0421	*0.0089*	-0.1195	*0.0153*
Social Awareness	-0.0203	*0.0042*	-0.0386	*0.0093*	-0.0185	*0.0054*	-0.0386	*0.0093*
Sum of Coefficients	0.1199	na	0.1555	na	0.1318	na	0.1555	na
SD of Prediction	0.0908	na	0.1083	na	0.0950	na	0.1083	na
Transitory SEL								
Self Efficacy	0.0135	*0.0027*	0.0135	*0.0027*	0.0266	*0.0064*	0.0266	*0.0064*
Self Management	0.0056	*0.0023*	0.0056	*0.0023*	0.0068	*0.0042*	0.0068	*0.0042*
Growth Mindset	-0.0013	*0.0024*	-0.0013	*0.0024*	-0.0110	*0.0054*	-0.0110	*0.0054*
Social Awareness	0.0037	*0.0019*	0.0037	*0.0019*	0.0036	*0.0032*	0.0036	*0.0032*
Sum of Coefficients	0.0215	na	0.0215	na	0.0260	na	0.0260	na
SD of Prediction	0.0104	na	0.0128	na	0.0121	na	0.0148	na

Appendix B.3. The Standard Deviations of SEL and Attendance Variables with and without Measurement Error Correction, Pooled Samples, Pre- and Post-Pandemic Periods

	Self Efficacy	**Self Management**	**Growth Mindset**	**Social Awareness**
Pre-Pandemic Period				
SEL Variables SD				
Student Average (No MEC)	0.745	0.854	0.813	0.928
Student Stable Component (with MEC)	0.641	0.744	0.673	0.779
Transitory Component (No MEC)	0.538	0.593	0.637	0.714
Transitory Component (with MEC)	0.554	0.605	0.679	0.748
Attendance Variable, Transformed	Mean	2.120	SD	0.420
Raw Attendance	Mean	0.975	SD	0.031
Post-Pandemic Period				
SEL Variables SD				
Student Average (No MEC)	0.738	0.811	0.801	0.896
Student Stable Component (with MEC)	0.632	0.684	0.671	0.729
Transitory Component (No MEC)	0.538	0.617	0.616	0.734
Transitory Component (with MEC)	0.557	0.646	0.647	0.782
Attendance Variable, Transformed	Mean	1.699	SD	0.487
Raw Attendance	Mean	0.937	SD	0.062