Title	Secondary quantitative analysis of core research data (2004-2010): A multilevel study of academic achievement and 21st century competencies
Author(s)	Melvin Chan and Jennifer Tan

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This study was funded by Singapore Ministry of Education (MOE) under the Education Research Funding Programme (OER 20/14 CCY) and administered by National Institute of Education (NIE), Nanyang Technological University, Singapore. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Singapore MOE and NIE.

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Version: 17 Jul 2020, NIE OER

EDUCATION RESEARCH FUNDING PROGRAMME

PROJECT CLOSURE REPORT

Secondary Quantitative Analysis of Core Research data (2004-2010): A Multilevel Study of Academic Achievement and 21st Century Competencies

By

Principal Investigator:
Dr Melvin Chan

Co-Principal Investigators:
Dr Jennifer Tan

National Institute of Education
Singapore

EXECUTIVE SUMMARY (NO MORE THAN 5 PAGES)

INTRODUCTION/BACKGROUND

The Core Research Programme is a large-scale representative study of teaching, learning and cognitive assessment practices and student outcomes. Within this major project, survey and assessment data were collected across three subsidiary projects. Core 1 Panel 2 (2004) and Core 2 Panel 2 (2010) are two unique datasets that focus on how school, classroom and student level factors contribute to individual variation in student achievement and other key 21st century (21C) learning outcomes. Core 1 Panel 6 (2008), on the other hand, is another study that captures a broader range of affective, educational and psychosocial factors.

The overall objective of this proposed study is to undertake secondary quantitative analyses of student achievement and selected 21C (non-academic) learning outcomes using existing datasets from the Core Research Programme. First, the proposed study will investigate and compare the proportion of variation in student achievement data and background characteristics across Singapore classrooms and schools. Next, we will investigate, identify and compare the extent to which the variability in student achievement is influenced by student, classroom and school level factors. Third, by linking two datasets, the proposed study will investigate the longitudinal impact of Primary Six students' psychosocial and educational characteristics on their Secondary Three academic achievement and 21C (non-academic) learning outcomes.

The proposed study is important for a number of reasons. First, knowledge of the proportion of variance distributions provides important information for school effectiveness regarding expected shifts in the proportion of variation that can be attributed to different levels of analysis. In broader terms, shifts in variation also provide important information that addresses issues of social and educational equity, given practical difficulties in assessing the direct impact of educational policies. Second, since relationships among different educational variables are often interactional in nature, modelling key contributions of student, class and school level effects separately and simultaneously provides important information about which variable matters most for explaining student achievement, controlling for all other variables considered. Third, observations of individual characteristics and the prospective academic achievement and 21C (non-academic) learning outcomes among the same students over time can provide more robust information about important educational input and process factors.

STATEMENT OF PROBLEMS

Despite the richness of these datasets, however, existing research publications have been limited to cross-sectional analyses using data from individual datasets. Much too often, considerable time and resources go into the collection and analysis of large-scale data only to be archived at the end of a project or publication cycle. Even though new data may be collected from relatively similar methods of sampling and population profiles, research findings are often reported independently. This project aims to fill this gap by generating new data from combining existing datasets and identifying further gaps that may be useful for future research planning. More importantly, given the comparability of key measures and a largely similar sample of schools (especially for 2004 and 2010 Panel 2 datasets), the linking of multiple sources of data can provide a much richer research resource, develop new uses of existing datasets and generate new research questions that cannot be addressed without the combined information.

PURPOSE OF STUDY

The overall objective of this proposed study is to undertake secondary analyses of three interlinked datasets from the Core Research Programme. The overall focus of this study include 1) examining and comparing across multiple datasets the proportion of variability in student achievement across students, classrooms and schools; 2) examining and comparing across multiple datasets the proportion of variability in key compositional factors related to student achievement across classrooms and schools; 3) examining and comparing across multiple datasets key contributions of student, classroom and school level factors on variation in student achievement; and 4) examining the longitudinal impact of Primary Six students' psychosocial and educational characteristics on their Secondary Three academic and non-academic outcomes by combining information from the Core 1 Panel 6 (2007) and Core 2 Panel 2 (2010) datasets.

PARTICIPANTS

No data was collected as the study involved a secondary analysis of existing datasets.

Methodology / Design

Previous and preliminary analyses of the existing datasets have employed exploratory and confirmatory factor analysis to validate the underlying factor structures, while two-parameter IRT modelling was used to calibrate the 28-item mathematics and 70-item English achievement test items. Reliability of the achievement instruments across 2004 and 2010 was consistently in the range of .75 to .77 and .88 to .92, respectively. Given the aims of this research, the analysis will focus on hierarchical linear modelling (HLM) and multilevel structural equation modelling (MLSEM).

Findings / Results

Findings of this study showed that there are meaningful variations in student achievement across different units of analysis, namely, variations at the student, class and school level. Drawing on a comparative analysis of two large-scale cohorts (P5 and S3) and periods (2004 and 2010), we found an increase in classroom effects which are consistent with current empirical research and perspectives in the educational effectiveness literature that classrooms matter more than schools. In 2004, the strongest predictor of achievement at the school level was behavioural management (i.e., a collective sense that teachers in the school ensure the good behaviour of students, create a conducive classroom environment for learning, correct misbehaviour and are in control of the class). In 2010, the strongest predictor of both classroom and school level effects on achievement was structure and clarity (i.e., instruction that emphasizes coherence and clarity of lesson goals). However, compositional effects due to students' family background and prior achievement continue to have a sizeable impact on student outcomes. This could be reinforced by stream effects and allocation of students to classes on the basis of prior achievement, which are common school practices in Singapore (at least between 2004 and 2010). Our longitudinal data (drawn from a subsample from two datasets) indicated that Primary school indicators (specifically, school academic ranking) have little influence on subsequent outcomes, while student background factors continue to make a significant impact.

Contributions

First, we utilised value-added multilevel models to examine the proportion of observed variation in student achievement and background factors that can be attributed to differences across schools, classrooms and students. We confirm existing criticisms of school effect models and suggest that researchers pay greater attention to what goes on within schools. Second, our comparative analyses confirm that school progress is not static. While input and process indicators remain stable, others can vary in effectiveness over successive cohorts and periods. Therefore, a study of the research findings and their relevance to ongoing policy reforms can help policy researchers make better sense of what has changed and whether the plausible causes of those changes are in line with the expected outcomes. Third, this study provides available data that expands and deepens our understanding of the various socio-cultural effects on education and its relations with meritocracy.

Conclusion

Although this study examines existing data, it highlights the importance of continuing investigations about the stability and shifts in inputs and process factors and their impact on student educational outcomes. Because educational improvement often requires cumulative processes that build on incremental knowledge of causal factors and their consequent effects, findings from this study help to connect the empirical evidence base about effective indicators of Singapore classrooms and schools, and in doing so provide important clues for developing and monitoring research-informed strategies and focusses.

Acknowledgements

Please acknowledge the source of funding for all conference presentations and publications arising from this study in the following manner:

This study was funded by the Education Research Funding Programme, National Institute of Education (NIE), Nanyang Technological University, Singapore, project no. OER 20/14 CCY. The views expressed in this paper are the author's and do not necessarily represent the views of NIE.

Keywords

Positive student outcomes; academic achievement; Core research

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Principal Investigator:
Dr. Melvin Chan

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The overall objective of this proposed study is to undertake secondary quantitative analyses of student achievement and 21C (non-academic) learning outcomes using existing datasets from the Core Research Programme. First, the proposed study will investigate the proportion of variation in student achievement data and background characteristics across Singapore classrooms and schools. Next, we will investigate and identify the extent to which the variability in student achievement is influenced by student, classroom and school-level factors. Third, by linking two datasets, the proposed study will investigate the longitudinal impact of Primary Six students' psychosocial and educational characteristics on their Secondary Three academic achievement and learning outcomes.

The proposed study is important for a number of reasons. First, knowledge of the proportion of variance distributions provides important information for school effectiveness regarding expected shifts in the proportion of variation that can be attributed to different levels of analysis. In broader terms, shifts in variation also provide important information that addresses issues of social and educational equity, given practical difficulties in assessing the direct impact of educational policies. Second, since relationships among different educational variables are often interactional in nature, modelling key contributions of student, class and school level effects separately and simultaneously provides important information about which variable matters most for explaining student achievement, controlling for all other variables considered. Third, observations of individual characteristics and the prospective academic achievement and learning outcomes among the same students over time can provide more robust information about key educational input and process factors.

STATEMENT OF PROBLEMS (I.E., JUSTIFICATION FOR THE STUDY)

Despite the richness of these datasets, however, existing research publications have been limited to cross-sectional analyses using data from individual datasets. Much too often, considerable time and resources go into the collection and analysis of large-scale data only to be archived at the end of a project or publication cycle. Even though new data may be collected from relatively similar methods of sampling and population profiles, research findings are often reported independently. This project aims to fill this gap by generating new data from combining existing datasets and identifying further gaps that may be useful for future research planning. More importantly, given the comparability of key measures and a largely similar sample of schools (especially for 2004 and 2010 Panel 2 datasets), the linking of multiple sources of data can provide a much richer research resource, develop new uses of existing datasets and generate new research questions that cannot be addressed without the combined information.

PURPOSE OF STUDY (INCLUDING RESEARCH QUESTIONS AND/OR OBJECTIVES)

The overall objective of this proposed study is to undertake secondary analyses of three interlinked datasets from the Core Research Programme. The overall focus of this study include 1) examining and comparing across multiple datasets the proportion of variability in student achievement across students, classrooms and schools; 2) examining and comparing across multiple datasets the proportion of variability in key compositional factors related to student achievement across classrooms and schools; 3) examining and comparing across multiple datasets key contributions of student, classroom and school level factors on variation in student achievement; and 4) examining the longitudinal impact of Primary Six students’ psychosocial and educational characteristics on their Secondary Three academic and non-academic outcomes by combining information from the Core 1 Panel 6 (2007) and Core 2 Panel 2 (2010) datasets.

Research questions are as follows:

1) How much of the variation in student achievement is distributed within classrooms, between classrooms within schools and between schools? Specifically, do the variance distribution in student achievement differ by academic subject (English or Mathematics), by the level of education (Primary Five and Secondary Three) and by cohort (2004 to 2010)?
2) How much of the variation in student socio-economic status and prior attainment is distributed within classrooms, between classrooms within schools and between schools? Specifically, do the variance distribution in student socio-economic status and prior attainment differ by cohort (Primary Five and Secondary Three) and by period (2004 and 2010)?
3) What are the key contributions of student, class and school level effects on variations in student achievement? Additionally, do these effects differ across period cohorts (2004 versus 2010)?
4) What are the key factors that facilitate students' attainment of academic and non-academic outcomes, controlling students' background and prior school experiences?

PARTICIPANTS

No data was selected as the analysis involved the use of three existing datasets. Two large-scale cross-sectional datasets were obtained from *Core 1 Panel 2 (2004)* and *Core 2 Panel 2 (2010)*. Participants from these datasets were Primary 5 and Secondary 3 students across approximately 39 schools at each level. The third dataset was longitudinal. We generated this unique dataset by matching student IDs of Primary 6 (P6) students in *Core 1 Panel 6 (2007)* with Secondary 3 (S3) students in *Core 2 Panel 2 (2010)*. A sample of 871 students was matched which were represented across 38 Primary (P6) schools [in Panel 6 2007] and 29 Secondary schools (S3) [in Panel 2 2010].

METHODOLOGY/DESIGN

An overview of measures used (for this report) across different datasets can be found in Table A6. Previous and preliminary analyses of the existing datasets have employed exploratory and confirmatory factor analysis to validate the underlying factor structures, while two-parameter IRT modelling was used to calibrate the 28-item mathematics and 70-item English achievement test items. Reliability of the achievement instruments across 2004 and 2010 was consistently in the range of .75 to .77 and .88 to .92, respectively. Given the aims of this research, the analysis will focus on hierarchical linear modelling (HLM) and multilevel structural equation modelling (MLSEM).

FINDINGS / RESULTS

RQ 1: *How much of the variation in student achievement (English and mathematics) is distributed within classrooms, between classrooms within schools and between schools (P5 and S3 cohorts)?*

Summary of key findings:

i) Using residual plots of estimated school effects (two-level model), our findings (see Figures A1-2) revealed that school effects exist as depicted in the residual plots. However, after taking class-level effects, the majority of these differences reside within schools, between classes.

ii) Using three-level the intraclass coefficients (ICC) models (see Figure A3), our findings showed that, in the case of S3 English achievement, school-level (L3) variation increased from 20% in 2004 to 22% in 2010. This suggests that the attribution of English achievement to differences between schools remains quite substantial, after taking into account L2 variation.

iii) In the case of S3 math achievement, L3 variance decreased from 15% to 9%. Therefore, schools are more different with respect to English achievement.

iv) In the case of P5s (English and mathematics), small L3 variation was observed; however, note the larger L2 variance highlighted below (see point v). Compared to Secondary schools, Primary schools are more homogenous with respect to their influence on academic achievement.

v) Despite moderate fluctuations, L2 (class-level) variation in academic achievement remains very substantial across both cohorts and subjects. Average L2 variance range from 54-67% for P5s and 35-51% for S3s. It should be noted that while P5 L2 variance increased (by 3-14%), indicating stronger within-school variation, S3 L2 variance decreased (by 5-9%), though the latter remained sizeable.

vi) L1 variance follows a similar distributive pattern to L2. Average L1 variance ranged 30-40%.

Key Findings Explained.

Residual plots. Using residual plots to estimate school effects (see Figures A1-2), we found that approximately a third or less of Primary schools show an overlap of intervals (covering the mid-point of zero) in English and mathematics performance, suggesting on the onset that schools differ substantially on academic performance. On the contrary, the majority of Secondary schools showed substantial overlap, suggesting that academic performance, at least at the S3 level, remains relatively similar across Secondary schools. However, we caution against quick assumptions of overall school effects without due consideration of factors inherent within schools. Importantly, it should be noted that while Primary schools were quite different with respect to academic performance, the confidence intervals were visibly wide (suggesting unaccounted within-school effects). We provide supporting evidence in the next set of findings which reveal large variations among the ICC estimates of three-level models. In addition, there were also visible variations in achievement among schools that participated in both 2004 and 2010 studies. In Table A1, we present a comparison of shifts in academic achievement and SES, as well as PSLE grades (for S3), over a 6-year period. Some schools (e.g., P5 School A, B) experienced achievement gains in both subjects, despite lower School SES. Some, however, showed improvement gains but in one subject. Among the S3 schools, improvement in English was consistent with better PSLE grades and SES. On the other hand, improvement in mathematics achievement had less association with higher PSLE grades. While these comparisons were not necessarily representative, they provide some evidenced-based suggestions that school achievement, as well as their inputs and processes, do indeed vary overtime. Our findings, therefore, highlight the importance of taking into account within-school effects. In summary, school effects exist as depicted in the residual plots, but our findings also showed that these differences reside primarily within schools, between classes. Points ii to vi illustrate the importance of accounting for classroom effects using three-level models.

Primary 5 (P5) English: Drawing on repeated cross-sectional datasets (2004 and 2010), a 3-level multilevel model (see Figure A3) was performed to examine the distribution of explanatory variance (i.e., the ICCs) across each level (Figure A3). In multilevel studies, thresholds of 15%, 10% and 5% are typically used to interpret a large, medium and small effect size (Hox, Moerbeek & van de Schoot, 2010). Findings indicated that the majority of the variation in English achievement was located at Level 2—classrooms. Between 2004 and 2010, L2 variance increased by 3% between 2004 (64%) and 2010 (67%), variance at L1 dropped by 3% (35% and 33% respectively), while school-level variance (L3) remained stable at less than 1%. This suggests a stronger within-school effect. Another interesting observation was the increased variance around the variance decomposition estimates (i.e., the ICC). For instance, variance deviation for achievement in 2004 were .387 (L1) and .687 (L2), while they were .503 (L1) and 1.042 (L2) in 2010. This suggests a widening (or longer tail) distribution of achievement performance over time. Indeed, Figure A2 shows the "caterpillar" plots for each cohort. Across all schools, the spread of the "whiskers" was wider in 2010.

Secondary 3 (S3) English: In contrast to P5 English, variance at L1 (student) and L3 (school) increased. At L1, explained variance increased by 8% (35% at 2004 and 43% at 2010). At L3, explained variance increased by 2% (20% at 2004, and 22% at 2010). However, L2 (classroom) decreased by 5% (45% and 40%, respectively).

P5 Mathematics: Consistent with P5 English, the majority of the variation in P5 mathematics achievement was located at L2 (classroom). However, differences in explanatory variance were larger, compared to English. Between 2004 and 2010, there was a substantial increase in L2 variance of 14% (54% in 2010 and 68% in 2010). L3 and L1 variance also decreased but by a larger proportion. At L3, the decrease was 4% between 2004 (4%) and 2010 (0%). At L1, the decrease was 10% (42% in 2004 and 32% in 2010). Similarly, we also observed increased variance around the variance decomposition estimates. For instance, variance deviation for achievement in 2004 were .367 (L1) and .477 (L2), while they were .401 (L1) and .841 (L2) in 2010.

S3 Mathematics: Consistent with P5 mathematics (in which L3 variance decreased by 4% overtime), L3 variance for S3 mathematics decreased by 6%, from 15% in 2004 to 9% in 2010. However, in contrast to P5 in which there was a substantial increase of 14% in the L2 variance, for S3, L2 variance decreased by 9%, from 51% in 2004 to 42% in 2010. Similarly, in contrast to the decrease in L1 variance among P5s overtime, L1 variance increased by 14% for the S3 cohort over time.

<u>Implications:</u> Based on the descriptive but comprehensive multilevel analyses, there are three implications for research and policy. First, our findings from the residual plots and subsequent three-level models support a longstanding criticism of value-added models of adjusted school effects that evaluate schools on performance on the basis of certain school-level input characteristics without sufficient attention to within-school processes (Amrein-Beardsley, 2014). Therefore, the use of two-level models which are typically employed in large-scale multilevel studies may provide imprecise estimates about the actual effects attributable to school inputs and processes.

Second, from a research validity standpoint, our data provides high comparative value to inform international research. The estimates of variance decomposition from the 2010 data are closely consistent with comparative estimates reported by Hattie (2009) who concluded that, on average, students, classrooms and schools explain about 44%, 49% and 23% of the variation in student achievement.

Third, from an education policy perspective, reducing institutional differentiation (on the basis of academic performance) is an important educational goal. When achievement is less dependent on the social characteristics of the school that students attend, students are afforded the similar opportunities (and environment) for maximising learning and achievement. In systems with limited institutional differentiation, each school and teacher will make available and promote a full range of student competencies and academic interests regardless of prior ability and background. Evidence from the P5 cohort is a case in point. With reducing L3 variation over time, L2 effects (i.e., teacher, classroom instruction) increased.

RQ 2: *How much of the variation in student socio-economic status and prior attainment is distributed within classrooms, between classrooms within schools and between schools? Specifically, do the variance distribution in student socio-economic status and prior attainment differ by cohort (Primary Five and Secondary Three) and by period (2004 and 2010)?*

Analytical Approach. The analysis of nested educational data (i.e., students who share the same educational context—same classroom, same school) often draws attention to the influence of contextual effects (i.e., group-level characteristics) and how to impact individual-level outcomes, beyond what could be explained by individual-level characteristics (Harker & Tymms, 2004). Therefore, the analyses conducted to address this research question employ multilevel analytical techniques to account for the unique contribution of individual and compositional characteristics (of socio-economic status and prior attainment) on student achievement outcomes. Extending the findings of RQ1, we examined distributions of the social characteristics of school over time for the P5 and S3 cohorts. We created a Socio-economic (SES) index as a weighted composite of mothers' educational level, type of residence (1-room HDB to Landed property) and SES resources (family has a domestic helper, a car and owns country-club memberships). PSLE aggregate scores were used for the analysis examining variations in prior attainment.

Summary of Key Findings: Students' family SES matters (see Figure A4). Although between-school SES variance decreased for the P5 cohort, it remained very substantial, averaging 18% over a 6 year period. Similarly, for S3s, between-school SES variance was also in the moderate range, from 10-12%. However, while RQ1's findings indicated that the majority of the within-school achievement effects was located at L2 (i.e., classrooms), the majority of the within-school SES effects was located at L1 (i.e., students). With respect to prior attainment, the findings were more consistent with RQ1's. Together, the findings on S3 students' achievement and background characteristics and their attribution to school-level effects indicate that schools are converging on academic performance, but remain quite different with respect to SES characteristics.

Key Findings Explained.

P5 Cohort (variation in SES): From Figure A4, L3 SES variance decreased by 4% (20% in 2004 and 16% in 2010), but L2 SES variance increased by 2% (7% in 2004 and 9% in 2010), and L1 SES variance increased 3% (73% in 2004 and 76% in 2010). Although between-school differences dropped slighted, it remained very sizeable, thus, suggesting that Primary schools are not very homogenous with respect to SES levels. Therefore, certain schools do attract more students from privileged families.

S3 Cohort (variation in SES): From Figure A4, L3 SES variance increased by 2% (10% in 2004 and 12% in 2010), but L2 decreased 2% (9% in 2004 and 7% in 2010), while there was no change for L1 (81% in 2004 and 2010). This suggests that differences in school-level SES remain quite substantial across schools. Therefore, certain schools attract more students from privileged families. The slight drop class-average SES indicates that S3 classrooms are becoming less homogenous with respect to social class characteristics.

S3 Cohort (variation in prior attainment): This analysis attempts to examine changes in the profile of student quality across schools. Our findings reveal that student quality (measured by school-average PSLE T-scores) remained relatively stable across schools. Between 2004 and 2010, L3 explanatory variance for prior attainment was 24% and 22% respectively. L2 variance was 60% and 64%, and L1 variance was 16% and 14%, respectively, across 2004 and 2010. These findings suggest a high concentration of similar ability students in the same classrooms.

Implications. In general social science literature, educational inequalities are often attributed to differences in social class and family background. RQ2's findings indicate that between-school SES variance at the Primary level remains quite substantial. At the Secondary level, however, the variance is lower, which suggests a possibility that inequalities due to family SES-related effects may have shifted towards more merit-based "ability-driven" factors (i.e., prior attainment) as students move from Primary to Secondary education. Yet, the very strong between-class composition of PSLE scores at the S3 level, through which students are assigned to classes on the basis of their prior attainment, may be a form of institutional "inequality", created due to existing class assignment practices. As later multilevel findings reveal, the class-average prior attainment (PSLE) has a very strong influence on S3 student achievement.

For instance, the multilevel correlations were approximately .50 in English and .75 in mathematics. To reduce differentiation across classes, policies on class assignment in Secondary schools on the basis of prior attainment should be reviewed. Some empirical studies have shown that mixed ability groupings improve the learning outcomes of low- to average-ability students without necessarily affecting the performance of high-ability students.

RQ3: *What are the key contributions of student, class and school level effects on variations in student achievement? Additionally, do these effects differ across period cohorts (2004 versus 2010)?*

Extending from RQ2, we expanded the multilevel model by including additional contextual and explanatory variables representing each level of analysis. The purpose of this analysis was to examine a range of key input and process variables and their influence on student achievement in mathematics and to determine if cohort differences exist across the relationships, and if so which ones. In RQ1, we found that L2 and L3 ICCs were 51% and 15%, respectively. In multilevel modelling, these statistics represent the unconditional model (i.e., Model 0). In this analysis, two incremental statistical models were specified and compared across 2004 and 2010. Model 1 examined contextual input variables, while Model 2 included additional “process” variables (e.g., student learning dispositions, instructional and classroom climate). [*Note.* For this analysis, we focus on the S3 cohort due to small between-school variance for P5s, and on mathematics due to limited space in the format of the final report]

Summary of key findings. Table A2 reports the summary of statistical findings that make comparisons of two (2004 and 2010) 3-level multilevel models. While distributions of SES and prior attainment (PSLE) remain relatively stable overtime among the S3 cohort (findings from RQ2), there were sizeable compositional effects of aggregated prior attainment and SES at both the classroom and school level. This suggests that certain schools were more attractive to Secondary students who come from higher SES households and possess higher levels of prior attainment (i.e., PSLE). Additionally, compositional effects also existed between classrooms, highly plausibly the results of further academic stratification by prior academic performance (i.e., PSLE). Although SES effects were slightly smaller in 2010 (compared to 2004), PSLE grew in strength. In addition to compositional effects due to PSLE and SES, our findings also indicated a strong gender effect (favouring females) on achievement. Gender also varied across PSLE and SES effects. While “who you go to class with” matters, it matters more for females.

In 2010, mathematics self-efficacy was found to be an important predictor of achievement. This provides supporting evidence for the increasing influence of individual dispositions commonly associated with 21st century competencies. However, the significant but negative effects of maladaptive extrinsic motivation (performance avoidance goals) and mathematics anxiety flag areas of concern that should be monitored with more recent data. At the classroom level, mathematics achievement was predicted by teachers who provided *structure and clarity* in their instruction (i.e., instruction that emphasizes coherence and clarity of lesson goals). Teachers' practice of SNC, however, varied across classrooms as SNC was more visible in classrooms characterised by higher PSLE mathematics grades. Although the effects of other instructional variables were not supported with statistical significance, it is important to highlight that the results could be an artefact of statistical multicollinearity due to high correlations. For example, SNC and teacher formative feedback and positive classroom climate were highly correlated at .73, .77 and .82, respectively. Therefore, teachers who provided SNC in their instructional delivery were also likely to have used formative feedback and have created a conducive classroom for learning.

Key Findings Explained.

Mathematics Achievement (2004): Model 1. We summarized the results Our results in Table A2. Model 1 investigated the effects of gender, race, PSLE (T-scores) and SES. Subsequently, we modelled the effects of these variables at both the class and school level, with the exception of race which had negligible upper-level variances (ICC<.05). At L1, variations in students' race and PSLE scores were associated with mathematics achievement. Given the high L2 correlations among gender, PSLE and SES at L2 (.36 to .68), we respecified the L2 relationships to better represent a "causal" model as well as to control for multicollinearity that could affect the precision of the parameter estimates (Marsh et al., 2004). In our revised L2 model, class-PSLE is predicted by class-SES and class-SES is predicted by class-gender (males coded 0, females coded 1). Students attained on average .721 SD units higher in the standardized mathematics test if their class-average PSLE grade exceeded the average PSLE by a one letter grade. For better interpretability of this finding, we refer to the raw scores in which the mean and SD were 11.7 and 5.1, respectively. An increase of .721 SD is therefore approximately equivalent to 3.5 marks (out of 28). Put simply, students' mathematics achievement would be 12.5% higher if they studied in classrooms in which the class-average PLSE grade was one grade higher than the overall average.

The strong positive association between class-PSLE and class-SES (b=1.157) indicates that class-SES influenced mathematics achievement indirectly through higher PSLE mathematics grade.

Therefore, “who you go to class with” matters. Importantly, our L2 findings also indicated that background matters for females. Female students achieved better mathematics grades if they studied in classrooms characterized by higher class-average SES and PSLE. To further examine the strong gender effect in the 2010 student cohort, the same model was analysed separately for males and females (*note.* a multiple group analysis was considered but not suitable as gender was specified at the group level). Our analysis showed stronger SES and PSLE effects on mathematics achievement for the model with females. The strong gender effect (favouring females) is particularly interesting given the conventional view that males tended to do better in numerical subjects such as mathematics. However, our findings are consistent with recent large-scale evidence from TIMSS. Examining data from the last three administrations (2003, 2007 and 2011), Mullis et al. (2012) observed a widening gender gap (favouring females) in mathematics achievement among Singaporean students. Finally, the L3 model showed that only school-SES significantly predicted mathematics achievement.

Mathematics Achievement (2004): Model 2. Model 2 investigated the effects of a range of student, and aggregated classroom and school-level variables collected across 2004 and 2010. At L1, statistically significant relationships on achievement were found with intrinsic motivation (positive effect) and mathematics anxiety (negative effect). The effect of student PSLE and race significant in Model 1, were no longer significant. At L2 and L3, we examined a range of classroom instruction and climate variables that included memorization, drill, structure and clarity, review/revision of past lesson, teacher support for learning, constructive feedback, classroom behavioural management and focus on exam preparation. However, only L3 classroom behavioural management was statistically significant (i.e., a collective sense that teachers in the school ensure the good behaviour of students, create a conducive classroom environment for learning, correct misbehaviour and are in control of the class). That is, a collective sense that teachers in the school ensure the good behaviour of students, create a conducive classroom environment for learning, correct misbehaviour and are in control of the class.

Mathematics Achievement (2010): Model 1. At L1, only differences in race were statistically significant. At L2, compositional effects observed in the 2004 model were generally weaker in magnitude, but still substantial, statistically significant and in the same direction. Females in classrooms in which the class-average SES and PSLE were higher, achieved better mathematics achievement. A series of test involving instructional and climate variables at L2 was not statistically significant. At L3, we observed a weaker influence of school-SES but a stronger influence of school-PSLE and school-gender. Although

SES effects remain robust, comparison of the 2004 and 2010 findings suggests that, over a 6-year period, and (highly plausibly) on the backdrop of reform initiatives towards a meritocratic and ability-driven education, attributions of student outcomes by social class background differences may have shifted to one in which individual abilities (e.g., prior achievement) and characteristics (e.g., gender, dispositions) are beginning to matter. Indeed, Model 2 provides supporting evidence for the increase influence of individual dispositions commonly associated with 21st century learning capacities.

Mathematics Achievement (2010): Model 2. At L1, the effect of student background characteristics on achievement remained constant. With the inclusion of student predictors, and compared to 2004, we observed a stronger influence of mathematics self-efficacy, but also extrinsic motivation (performance approach and avoidance) and mathematics anxiety. These findings warrant further investigation in the future given that extrinsic motivation and learning anxiety are often positively correlated in empirical research. At L2, compositional effects of prior attainment and SES remained robust. Among the range of instructional and climate variables examined, *Structure and Clarity* (SNC) positively predicted higher mathematics achievement (i.e., instruction that focusses coherence and clarity of lesson goals; e.g., “The Math teacher gives clear directions and explanations of the work we have to do”). Teachers’ practice of SNC, however, varied across classrooms as class-average PSLE math grades positively predicted SNC. Therefore, SNC would be .515 SD units higher (a meaningful effect) for students who study in classrooms in which the class-average PLSE grade was one grade higher than the overall average. Although the effects of additional instructional variables were examined, none were statistically significant. Given the high correlations, however, the lack of significance does not automatically rule out the substantive relevance of these variables. For example, SNC and teacher formative feedback and positive classroom climate were highly correlated at .73, .77 and .82, respectively. Therefore, teachers who provided SNC in their instructional delivery were also likely to have used formative feedback and have created a conducive classroom for learning.

At L3, compositional effects, including gender, continued to exert a substantial influence on school level mathematics achievement. Taking into account these variables, unexplained L3 variance dropped to appropriately 3%. Given the small variation left over, additional L3 analysis was no longer meaningful.

Implications. The findings above provide answers to persistent questions (and challenges) of educational inequality due to social class background. Although our findings show that these effects remain sizeable, comparisons of the 2004 and 2010 regression results suggest that over a 6-year period, and (highly plausibly) on the backdrop of reform initiatives towards a meritocratic and ability-driven education, attributions of student outcomes by social class background differences may have shifted to one in which individual abilities (e.g., prior achievement) and characteristics (e.g., gender, dispositions) are beginning to matter. Importantly, our findings from the 2010 dataset imply that learning dispositions and instructional practices were also beginning to matter more. This is consistent with empirical research and perspectives in the educational effectiveness literature (e.g., Kyriakes & Luyten, 2009). For instance, Hattie (2009) concludes that classrooms matter more than schools.

RQ4: *What are the key factors that facilitate students' attainment of academic and non-academic outcomes, controlling students' background and prior school experiences?*

For this research question, we combined two datasets to examine the longitudinal impact of Primary Six (P6) students' psychosocial and educational characteristics on their Secondary Three (S3) academic and non-academic outcomes. Based on a preliminary analysis of available variables and data, we expand RQ4 into two subsidiary questions that focus separately on the effects of schools and students: 1) What is the relative contribution of Primary and Secondary schools on students' achievement outcomes?; and 2) To what extent do students' background (including prior attainments and school experiences) influence subsequent academic and non-academic outcomes?

The longitudinal dataset comprises two datapoints: P6 and S3. In P6, students completed a survey assessing general learning dispositions and schooling experiences. Subsequently, at S3, the same students were assessed again. However, the S3 assessments involved a subject-specific survey and achievement test in mathematics. The final sample size for this dataset included 871 students (65% males) represented across 37 Primary schools (out of 39 in the 2007 study) and 30 Secondary Schools (out of 32 in the 2010 study). The outcome variable is S3 (2010) mathematics achievement.

For the first part of this analysis, we utilised a special case of multilevel modelling—cross-classified multilevel mixed-effects—to examine effects on achievement outcomes attributable to Primary and Secondary schools. Using Mplus software with Bayesian estimator, the analysis assesses the value-add of primary and secondary schools, for instance, do Primary schools have a long-term effect on subsequent student achievement and is there continuity of school effects on student achievement? This allows us to better assess the value-add of Secondary schools that adjust for initial students' achievement taking into account previous school membership (Goldstein & Sammons, 1997; Pustjens et al., 2007).

Key findings:

1) What is the relative contribution of Primary and Secondary schools on students' mathematics achievement?

For this analysis, we present individual residual plots (Figures A4-5) to examine the relative performance of Primary schools with respect to PSLE T-scores (standardised and self-reported in S3) and S3 mathematics achievement. While both plots show substantial overlap across Primary schools, the boxplots for S3 mathematics achievement were wider, suggesting a greater amount of variation when students enter Secondary school. Therefore, students who belong to the same Primary school can be expected to perform at a range of achievement levels at Secondary schools. Additionally, background factors (gender, race and prior attainment; race not significant in English model) continue to have a significant impact on S3 achievement. Given the importance of Primary school choices debated in public discourse, our findings show that students' future academic performance does not depend very strongly on the Primary school attended and other factors may be in play, for example, proximity, affiliation or values. Indeed, one preliminary analysis supports this observation. Based the 2004 MOE school ranking data (last year it was publicly available), the strength of the relationship between Primary and Secondary ranking was only modest at r=.29. Another analysis that examined the relationship between overall Primary school ranking and S3 mathematics achievement revealed that students who performed at least .5 SD above the grand mean came from Primary schools that ranked between 24 to 71 (1 being the top school and 158 being the lowest). Although our findings differ from prior research (e.g., Goldstein & Sammons, 1997), more recent research, however, reported a reduced Primary school effect (Pustjens et al., 2007).

Next, we specified a cross-classified multilevel model to examine these effects within an integrated model (see Table A3). In our analysis, we compared three types of models to estimate the contribution of Primary and Secondary school variance on S3 mathematics achievement: Primary school only, Secondary school only, and the Crossed model. Model 0 refers to the null model, while Model 1 includes additional background characteristics. The results indicate that differences across Secondary schools explain stronger variation in S3 achievement, and more so after taking into account key P6 student background characteristics. If the Secondary school hierarchy were ignored, the inflated (biased) estimate of the Primary school effect would be about two times its standard error [(.173/.036)/.068) in the crossed model. Therefore, the Primary school effect is not as large as previous studies have indicated (e.g., Goldstein & Sammons, 1997) and as public discourse suggests.

Table A4 summarises the results of the same analysis with English achievement. In general, similar conclusions could be inferred across both mathematics and English models.

2) To what extent do students' background (including prior attainments and school experiences) influence subsequent academic and non-academic outcomes?

In this analysis, three types of effect sizes are reported which correspond to the measurement characteristics of the predictor variables. Cohen's *d* and Omega Square (ω^2) are reported for comparing mean differences with two (t-test) and more than two groups (one-way analysis of variance), respectively. Third, ICCs are reported to examine the degree of stratification or clustering across schools. Due to space constraints, we focus our analysis on mathematics.

Examining the effect of school ranking on students' academic outcomes (using 2004 public data), we found mixed effects across Primary and Secondary levels. While Primary school ranking had a large effect on students' PSLE performance (ω=.117, p<.05)—the short-term effect— they had no influence on S3 Mathematics achievement (ω=.000, p>.05). On the other hand, while positive associations were found between students who did well in their PSLE and their placement in higher ranked Secondary schools (p<.05), the magnitude of the mean difference across three clusters of school ranking (i.e. top 50, 50-100 and >100) was small (ω=.027). Similarly, the effect size for S3 mathematics was also small (ω=.016).

Examining the effect of students' background on students' academic outcomes, we found that use of English at home had a significant influence on PSLE performance, associated with a moderate effect size (d=.301 for Fathers; d=.446 for Mothers). However, this linguistic or "cultural capital" advantage appears to taper off at S3 (p>.05). Finally, given persistent "folk" beliefs about the positive association between private tuition and academic success, we found weak evidence in support of this view. Based on three levels of frequencies, the influence of private tuition on PSLE was associated with a small effect size (ω=.031, p<.05). Moreover, private tuition at P6 also did not contribute to higher S3 mathematics achievement, thus, suggesting a lack of long-term impact on students' academic performance. Given research evidence on the positive association between academic self-beliefs and academic achievement, the significant effect of P6 private tuition on S3 mathematics self-beliefs (efficacy and self-concept) (ω=.017, p<.05) is noteworthy as it suggests a possible indirect relationship between private tuition and academic achievement that could motivate future research.

In terms of learning outcomes, we found negligible mean differences across most student and school characteristics, except gender. It is interesting to note that while females attained higher mathematics grades (PSLE and S3), they reported lower rating across several learning outcomes. Females reported lower competencies in Oral Communication, Use of Deep Thinking Strategies and Mathematics Self-Beliefs (self-efficacy and self-concept). Use of English with Mothers had a stronger influence on students' competency in Social and Leadership Skills (d=.259) (e.g., organising meetings, understand different opinions).

CONTRIBUTIONS OF STUDY

There are several contributions of this study. First, we utilised value-added multilevel models to examine the proportion of observed variation in student achievement and background factors that can be attributed to differences across schools, classrooms and students. We confirm existing criticisms of school effect models and suggest that researchers pay greater attention to what goes on within schools. Given increasing within-school (between class) variation, policies aimed at raising the academic grades of low achieving students, for example, is likely to be more effective if implemented within the school, taking into account pupils' profile and school culture, rather than a system-wide approach. Second, our comparative analyses confirm that school progress is not static. While input and process indicators remain stable, others can vary in effectiveness over successive cohorts and periods. Therefore, a study of the research findings and their relevance to ongoing policy reforms can help policy researchers make better sense of what has changed and whether the plausible causes of those changes are in line with the expected outcomes. Third, this study provides available data that expands and deepens our understanding of the various socio-cultural effects on education and its relations with meritocracy. While the (inequitable) impact of social class on educational outcomes is often inevitable, our comparative analyses over a 6-year period showed desirable shifts towards malleable individual characteristics and learning dispositions.

CONCLUSION

Although this study examines existing data, it highlights the importance of continuing investigations about the stability and shifts in inputs and process factors and their impact on student educational outcomes. Because educational improvement often requires cumulative processes that build on incremental knowledge of causal factors and their consequent effects, findings from this study help to connect the empirical evidence base about effective indicators of Singapore classrooms and schools, and in doing so provide important clues for developing and monitoring research-informed strategies and directions.

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APPENDIX

Table A1. Summary of *Comparisons of Differences in School Achievement (2004 vs 2010)*

P5 Schools	Difference in English Achievement	Difference in Mathematics Achievement	Difference in School SES
A	0.10	0.59	-0.05
B	0.44	0.37	-0.07
C	-0.04	0.21	-0.07
D	-0.01	0.20	0.03
E	-0.15	0.05	-0.26
F	--	-0.09	-0.12
G	-0.02	-0.31	-0.07
H	1.60	-1.26	-0.41

Note. Values are standardized scores. Composite for SES includes mother's educational level, type of residence and family economic resources.

S3 Schools	Difference in English Achievement	Difference in Mathematics Achievement	Difference in School SES	Difference in School PSLE English	Difference in School PSLE Math
A	.62	.14	-.11	.54	-.14
B	.55	--	.52	.50	.05
C	.20	-.23	.40	.55	.81
D	.14	.12	.13	.37	.10
E	.12	.10	.30	.28	.53
F	-.07	.21	.18	-.09	-.24
G	-.11	.27	.19	.33	-.12
H	-.12	.14	.14	-.09	-.06
I	-.18	.27	-.02	-.46	-.24
J	-.19	.08	-.09	-.47	-.06
K	-.22	.00	.77	-.15	.16
L	-.58	--	-.34	-.72	--

Note. Values are standardized scores. Composite for SES includes mother's educational level, type of residence and family economic resources.

Table A2. *Summary of Multilevel Regression Estimates of S3 Mathematics Achievement: 2004 versus 2010*

	2004		2010	
	Model 1	**Model 2**	**Model 1**	**Model 2**
	Estimate (Unstandardised)		**Estimate (Unstandardised)**	
Level 1 (Student)				
Gender	-.034	-.039	.028	.026
PSLE	.052**	.024^	.008	.004
Race	-.036*	-.034	-.089**	-.087**
SES	-.007	.006	.005	-.010
Intrinsic motivation		.074**		.018
Extrinsic motivation (approach)		.001		.060*
Extrinsic motivation (avoid)		-.031^		-.108**
Math self-efficacy		.036		.126**
Math anxiety		-.051**		-.098**
Level 2 (Class)				
Class-PSLE	.721**	.718**	.499**	.382**
Classroom Climate (Behavioural)		-.021		
Structural and Clarity (SNC)				.344**
Indirect effects				
Class-SES→Class-PSLE	1.157**	1.157**	.620**	.620**
Class-Gender→Class-SES	-1.734**	-1.734**	-1.138*	-1.138*
Class-PSLE → SNC				.197**
Level 3 (School)				
School-PSLE	-.008	-.039	.304*	.275*
School-SES	.473**	.556**	.161*	.149*
School-Gender	-.288	-.104	-.680*	-.608*
School Climate (Behavioural)		.627*		
Residuals				
U_{ijk}	.274	.267	.473	.448
U_{jk}	.077	.079	.287	.221
U_k	.117	.103	.018	.021
Model Fit				
Chi-square (df)	6.455 (3)	4.070 (5)	2.906 (3)	3.727 (5)
RMSEA	.017	.000	.000	.000
CFI/TLI	.979/.911	1.00/1.00	1.00/1.00	1.00/1.00
AIC	6425	3428	3076	3098

Note. ^p<.10. *p<.05, **p<.01. Given high correlations and variability across levels, groupmean centering was applied to PSLE and SES at L2. Unstandardised estimates are typically preferred for comparative analysis.

Table A3. *School Effect on Secondary 3 Mathematics Achievement*

	Model 0 (Pri School Only)	Model 1 (Pri School Only)	Model 0 (Sec School Only)	Model 1 (Sec School Only)	Model 0 (Crossed Model)		Model 1 (Crossed Model)	
Fixed Effects	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	***95% CI***	**Estimate**	***95% CI***
Female		.483*		.393*			.397*	*.234, .561*
Race		-.208*		-.207*			-.206*	*-.304, -.106*
Prior Achievement		.340*		.317*			.313*	*.252, .372*
Random Effects								
Student	.888* (.050)	.675* (.041)	.805* (.044)	.659* (.040)	.787* (.044)	*.706, .876*	.644* (.039)	*.574, .729*
Primary School	.173 (.068)	.062* (.030)			.036* (.025)	*.007, .103*	.029* (.021)	*.006, .085*
Secondary School			.239* (.090)	.087* (.042)	.222* (.087)	*.114, .443*	.074* (.042)	*.026, .184*

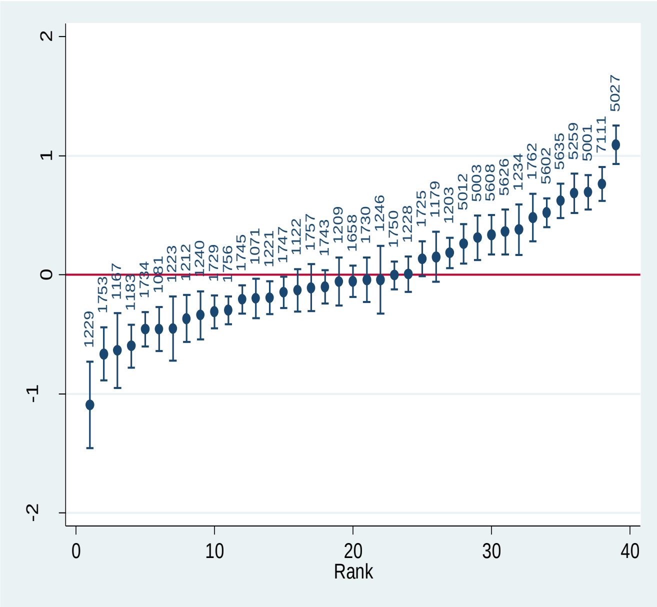
Note. **p*<.05

Table A4. *School Effect on Secondary 3 English Achievement*

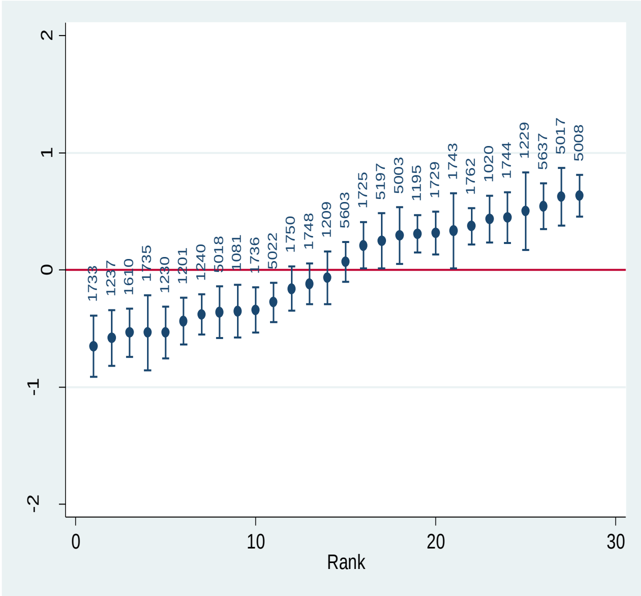
	Model 0 (Pri School Only)	Model 1 (Pri School Only)	Model 0 (Sec School Only)	Model 1 (Sec School Only)	Model 0 (Crossed Model)		Model 1 (Crossed Model)	
Fixed Effects	**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**	***95% CI***	**Estimate**	***95% CI***
Female		.329*		.334*			.320*	*.166, .476*
Race		-.043		-.068			-.047	*-.155, .054*
Prior Achievement		.355*		.301*			.311*	*.249, .372*
Random Effects								
Student	.806* (.049)	.576* (.039)	.717* (.044)	.565* (.039)	.680* (.042)	*.606, .769*	.542* (.037)	*.476, .621*
Primary School	.222 (.086)	.078* (.036)			.073* (.042)	*.019, .183*	.044* (.028)	*.013, .118*
Secondary School			.311* (.112)	.107* (.049)	.273* (.102)	*.145, .545*	.081* (.047)	*.025, .207*

Note. **p*<.05

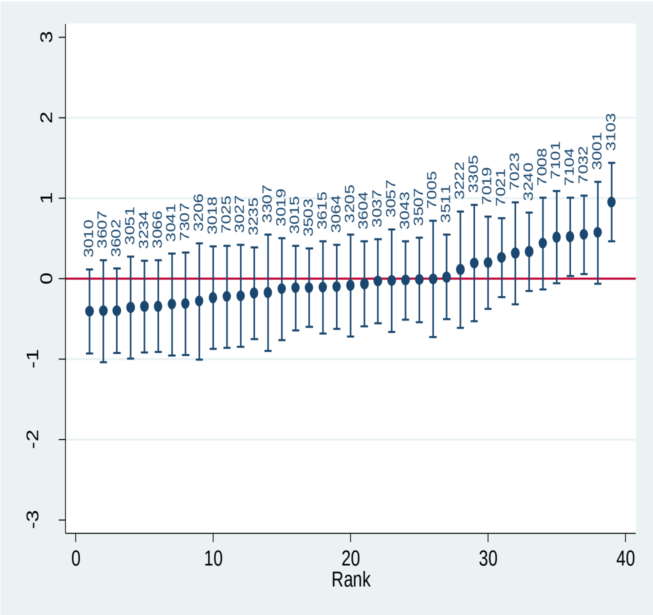
Figure A1. Residual Plots of Schools with 95% CI on English Achievement (2004 vs 2010)



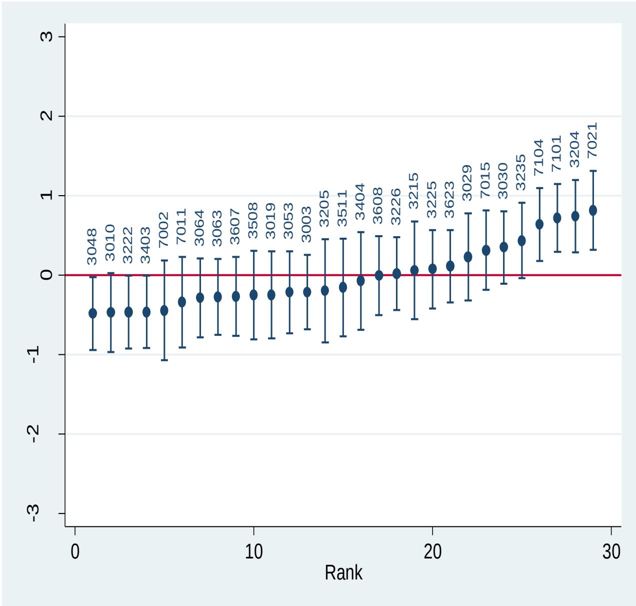
Random Effects of Schools on English Achievement for P5 students in 2004 (N=4,548)



Random Effects of Schools on English Achievement for P5 students in 2010 (N=2,966)



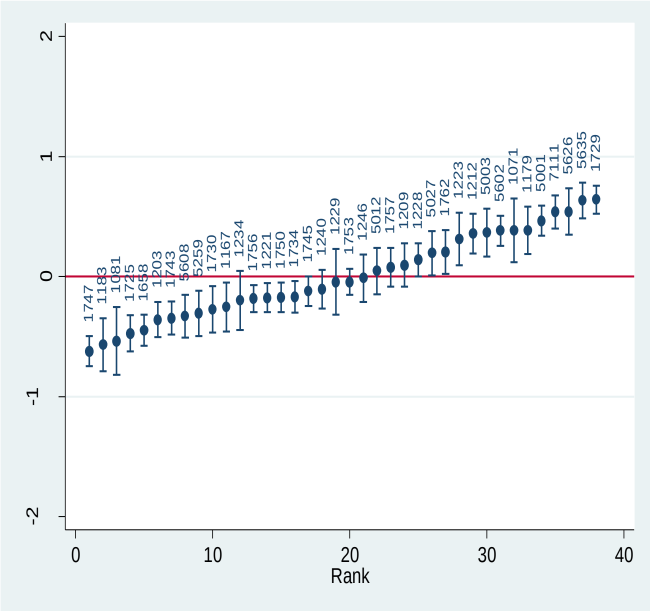
Random Effects of Schools on English Achievement for S3 students in 2004 (N=3,665)



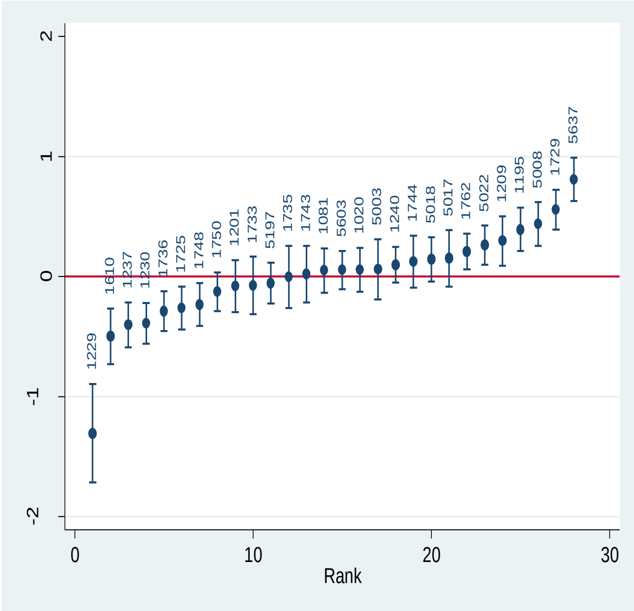
Random Effects of Schools on English Achievement for S3 students in 2010 (N=3,147)

Note. Schools are on the horizontal axis. Residuals of school achievement scores are on the vertical axis.

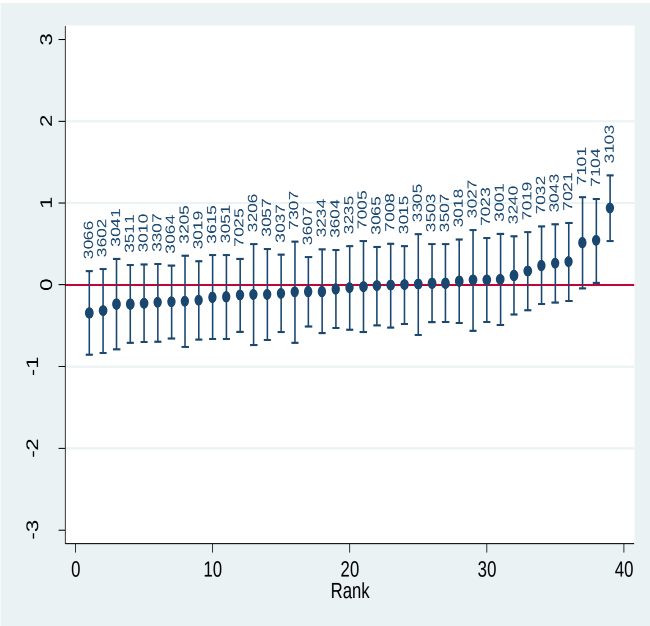
Figure A2. Residual Plots of Schools with 95% CI on Mathematics Achievement (2004 vs 2010)



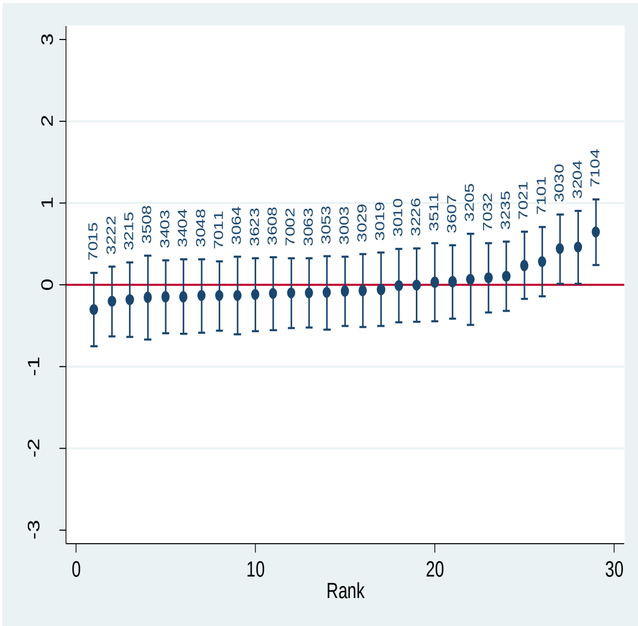
Random Effects of Schools on Mathematics Achievement for P5 students in 2004 (N=4,429)



Random Effects of Schools on Mathematics Achievement for P5 students in 2010 (N=2,966)



Random Effects of Schools on Mathematics Achievement for S3 students in 2004 (N=4,071)



Random Effects of Schools on English Achievement for S3 students in 2010 (N=3,452)

Note. Schools are on the horizontal axis. Residuals of school achievement scores are on the vertical axis.

Figure A3. *ICC for Achievement across Cohorts, Subjects and Period (2004 vs 2010)*

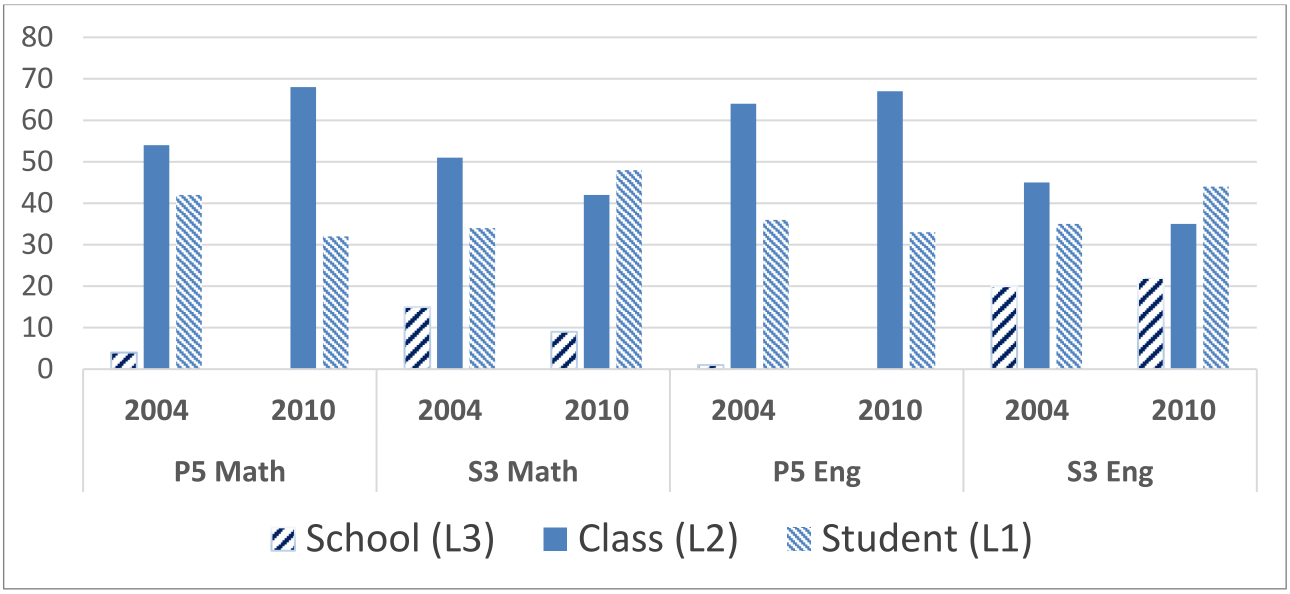


Figure A4. *ICC for Student SES across Cohorts and Period (2004 vs 2010)*

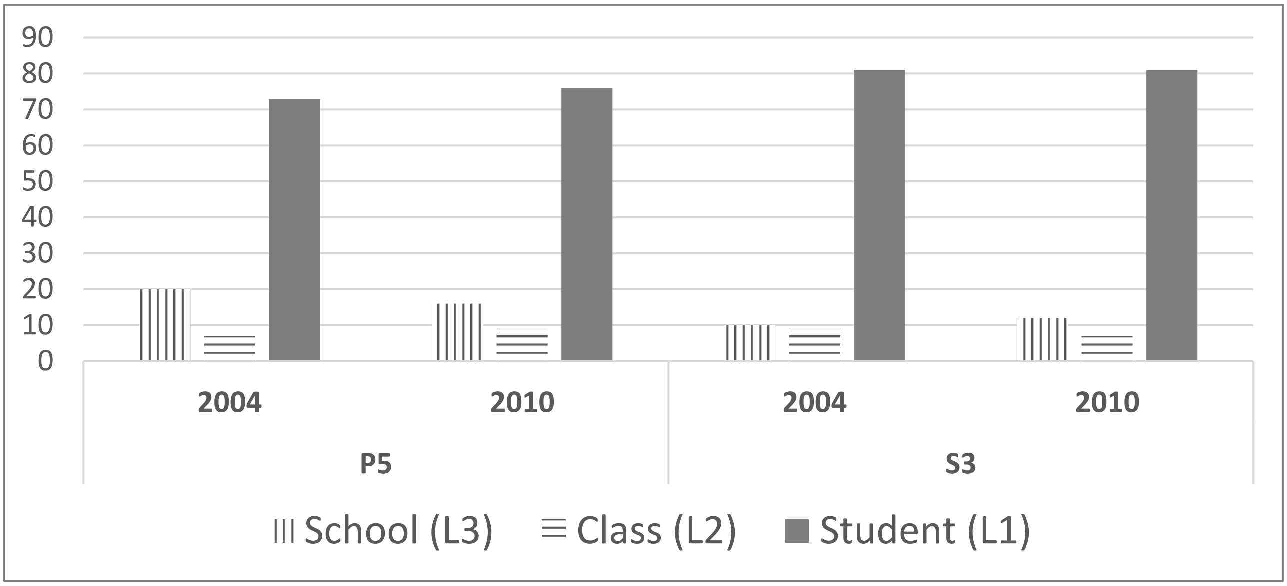
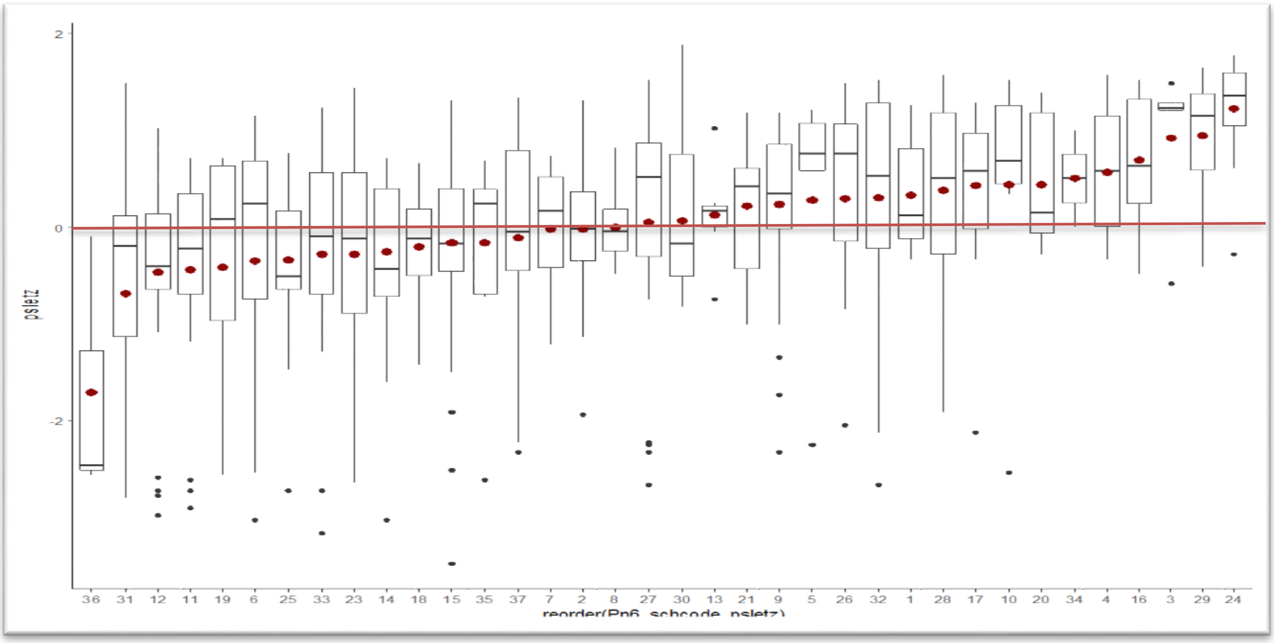
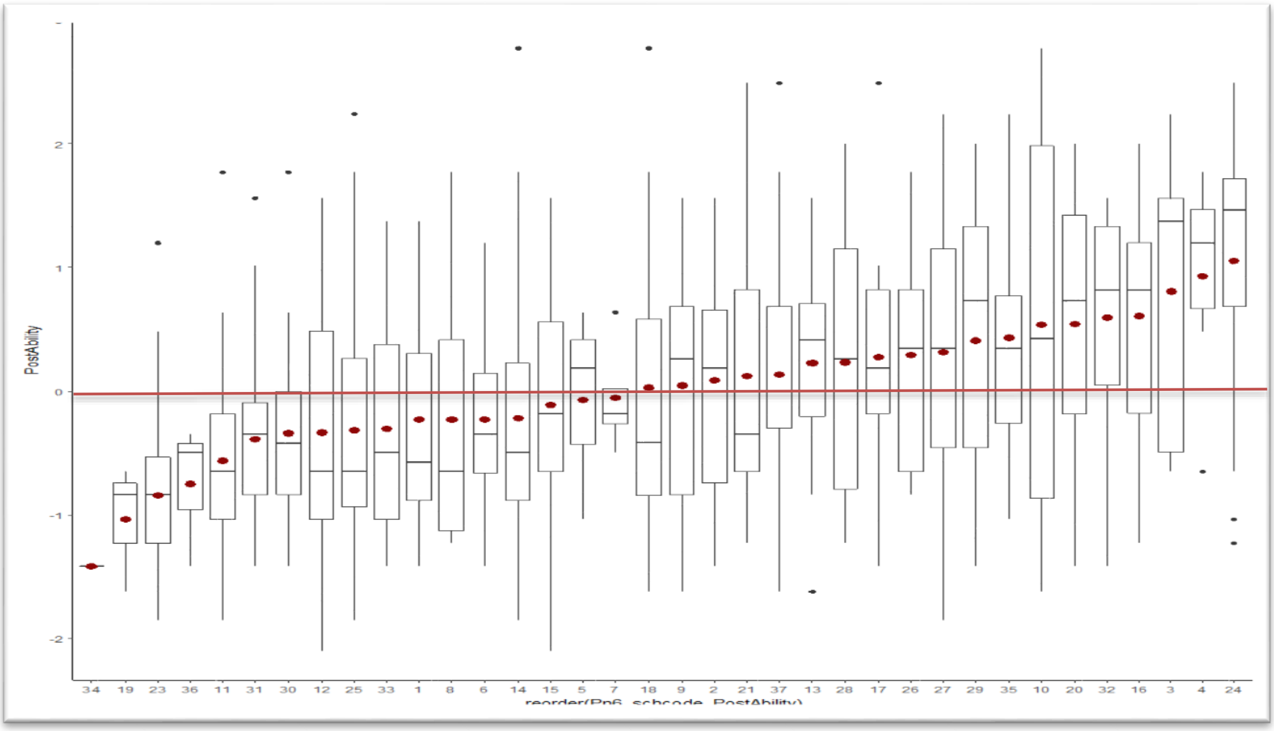


Figure A4. Residual Plots of P6 Schools with 95% CI on P6 PSLE Aggregate T-Score



Note. Schools are on the horizontal axis. Residual of PSLE T-scores are on the vertical axis.

Figure A5. Residual Plots of P6 Schools with 95% CI on S3 mathematics Achievement



Note. Schools are on the horizontal axis. Residual of PSLE T-scores are on the vertical axis.

Table A5. *Effect Size of Secondary Three Academic and Learning Outcomes by Primary* Six *Background Characteristics.*

	Academic Outcomes		**Learning Outcomes**							
	PSLE (N= 772-801)	***S3 Math (N= 864-893)***	***Cognitive Skills (N=369=381)***		***Intrapersonal Skills (N=369=381)***				***Interpersonal Skills (N=369=381)***	
Primary 6 Characteristics			*Oral Communication*	*Deep Processing*	*Math Self-beliefs*	*Mastery Approach Goals*	*Perform. Approach Goals*	*Metacognitive Regulation*	*Teamwork Collaboration*	*Social & Leadership*
[a]Gender	d=-.326*	d=-.499*	d=.387*	d=.387*	d=.142	d=.098	d=.100	d=.090	d=.009	d=.133
[b]SES (Pri)	ω=.038*	ω=.017*	ω=.001	ω=.000	ω=.003	ω=.001	ω=.001	ω=.000	ω=.006	ω=.000
[c]Stream (Pri)	ω=.305*	ω=.079*	ω=.005	ω=.000	ω=.009^	ω=.000	ω=.003	ω=.003	ω=.001	ω=.002
[d]School Rank (Pri)	ω=.117*	ω=.000	ω=.003	ω=.014*	ω=.020*	ω=.001	ω=.004	ω=.000	ω=.000	ω=.000
[e]Tuition per week	ω=.031*	ω=.000	ω=.000	ω=.001	ω=.017*	ω=.001	ω=.000	ω=.000	ω=.000	ω=.002
Speaks English:										
- with Father	d=.301*	d=.097	d=.187	d=.142	d=.013	d=.134	d=.021	d=.138	d=-.062	d=.167
- with Mother	d=.446*	d=.169^	d=.136	d=.091	d=.013	d=.095	d=.043	d=.082	d=-.041	d=.259*
Secondary 3 Characteristics										
[f]Stream (Sec)	ω=.715*	ω=.279*	ω=.000	ω=.000	ω=.018*	ω=.000	ω=.001	ω=.000	ω=.005	ω=.001
[g]School Rank (Sec)	ω=.027*	ω=.016*	ω=.011	ω=.000	ω=.002	ω=.007	ω=.000	ω=.001	ω=.002	ω=.000
School Stratification										
[h]School (Pri)	ICC=.131	ICC=.106	ICC=.019	ICC=.064	ICC=.053	ICC=.013	ICC=.011	ICC=.026	ICC=.018	ICC=.007
[i]School (Sec)	ICC=.343	ICC=.205	ICC=.047	ICC=.023	ICC=.082	ICC=.027	ICC=.006	ICC=.031	ICC=.004	ICC=.004

Note. *p<.05; ^p<.10; "d" denotes Cohen's d effect size with values close to .2, .5 and .8 indicating small, medium and large effects, respectively (see Cohen, 1988). "ω" denotes omega with values close to .01, .06 and .14 indicating small, medium and large effects, respectively (see Kirk, 1996). "ICC" denotes Intraclass Correlation with .05 as threshold for non-trivial effect size. All ICCs were estimated with the Bayes estimator.
[a]Reference is female;
[b]Based on family residence: 1=3rm HDB or smaller (N=162); 2= 4rm HDB (N=330); 3=5rm HDB (N=231); 4=Private (N=168);
[c]1=With higher mother tongue; 2=Without higher mother tongue; 3=EM3;
[d]1=Top50 (N=320; 12 schools); 2=51-100 (N=257; 10 schools); 3=Above 100 (N=314; 14 schools);
[e]1=None (N=182); 2=1-3 hours (N=367); 3=>4 hours (N=350).
[f]1=Express; 2=Normal (Academic); 3=Normal (Technical);
[g]1=Top50 (N=349; 10 schools); 2=51-100 (N=314; 12 schools); 3=Above 100 (N=218; 9 schools);
[h]School N=36; Within School N=4-104);
[i]School N=32; Within School N=3-111);

Table A6. *Overview of Measures across Datasets.*

	Panel 2 2004		Panel 2 2010		Panel 6 2007
	P5	S3	P5	S3	
[1]Achievement Tests:					
English		✓		✓	
Mathematics		✓		✓	
Background:					
SES	✓	✓	✓	✓	✓
Gender	✓	✓	✓	✓	✓
PSLE		✓		✓	
Stream				✓	
[2]School rank				✓	✓
Tuition per week					✓
Speaks English					✓
Survey Variables (L1):					
Intrinsic motivation		✓		✓	
Extrinsic motivation (approach)		✓		✓	
Extrinsic motivation (avoid)		✓		✓	
Math self-efficacy		✓		✓	
Math anxiety		✓		✓	
Survey Variables (L2):					
Structural and Clarity (SNC)				✓	
Positive Classroom Climate (Behavioural)				✓	
Classroom Feedback				✓	
Memorization				✓	
Drill				✓	
Focus on Exam Preparation				✓	
Teacher Review				✓	
Supportive Teacher				✓	

✓ denotes measures used in the analysis. [1] The same age-graded subject tests were administered. Same test for P5 2004 and 2010; S3 2004 and 2010. [2] Obtained from 2004 (last public data from MOE)