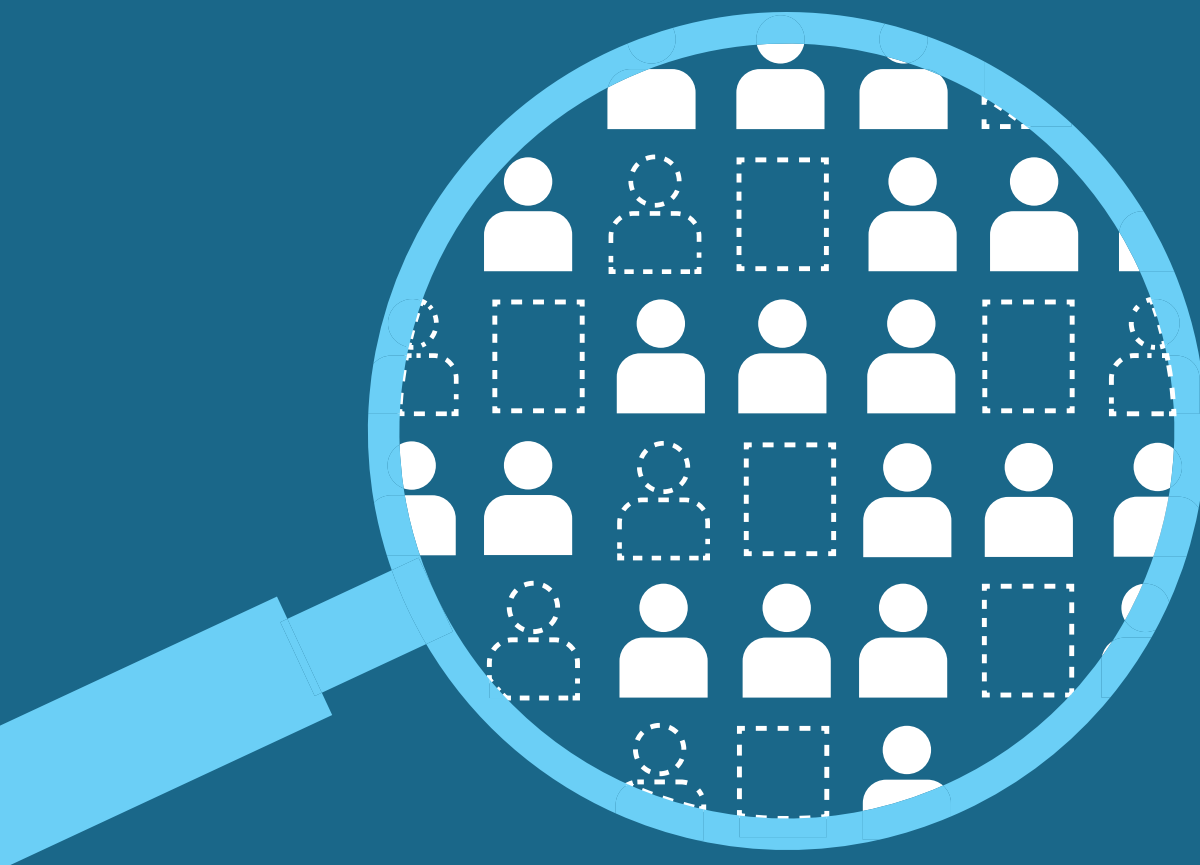


Student Absenteeism and Academic Achievement:

EVIDENCE FROM THE TIMSS 2023 LONGITUDINAL STUDY

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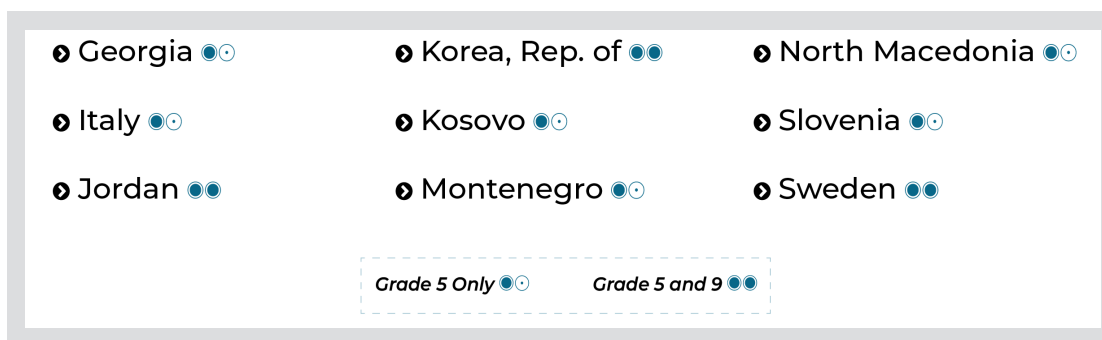
Student Absenteeism and Academic Achievement: Evidence from the TIMSS 2023 Longitudinal Study

Introduction

Regular school attendance has long been considered fundamental to student learning. Students' reports of school absences have been collected in TIMSS since the 2015 cycle and have consistently shown strong relationships with achievement in mathematics and science. Students who report rarely or never being absent from school show higher achievement in both subjects than students who report more frequent absences, across countries and assessment cycles.^{1,2,3,4} The TIMSS 2023 Longitudinal Study provides an opportunity to examine student absences from a different perspective, with data collected from the same students at two time points. This report uses students' reports on school absences across two school years (Grades 4 and 5) to shed additional light on the relationship between student reports on school attendance and students' progression of academic achievement for the nine countries participating in TIMSS 2023 Longitudinal. Students who report more frequent absences tend to have lower performance than their peers. We expect that the longitudinal results presented in this report will be of interest to both policymakers and researchers as the report shows how this general finding develops across multiple grades of primary school.

TIMSS 2023 Longitudinal is the first international student-level longitudinal extension of TIMSS (Trends in International Mathematics and Science Study). Education systems participating in the longitudinal study tracked the Grade 4 and Grade 8 students who participated in TIMSS 2023 and reassessed them one year later in 2024 (in Grade 5 or 9). Students completed the mathematics and science assessment a second time, and the TIMSS 2023 contextual questionnaires were also updated and readministered as part of this effort, allowing for measuring both students' achievement growth and relevant contextual factors over time. The education systems that participated in TIMSS 2023 Longitudinal are shown in Exhibit 1 and further information about the study is available in the [TIMSS 2023 Longitudinal International Results in Mathematics and Science](#) and the other relevant publications listed in [Appendix A: About TIMSS 2023 Longitudinal](#).

Exhibit 1: TIMSS 2023 Longitudinal Participants



This Insights report builds on the [findings related to student absences that are presented in the TIMSS 2023 Longitudinal International Results](#), which show a negative association between student reports of school absences and achievement in mathematics and science, as well as growth in these subjects. As an initial foray into investigating the longitudinal data, this report focuses specifically on examining this topic using descriptive statistics and results from a hierarchical linear modeling analysis. The structure of the longitudinal data provides a unique opportunity for this type of exploration because both achievement and contextual data are available for two consecutive years, whereas only cross-sectional data are available in a typical TIMSS cycle.

Overview of Report Contents

This Insights report begins with an overview of the importance of students' presence at school for promoting student learning and continues with a review of selected literature examining the relationship between student absences and academic achievement. In particular, the review focuses on secondary research using data from prior TIMSS cycles, as well as research using longitudinal data. The report then presents an exploration of TIMSS 2023 Longitudinal data on student absences, focusing on characterizing patterns of students' reported absences in 2023 and 2024 (across Grades 4 and 5). The student absence classifications derived from this exploration serve as the basis for a hierarchical linear modeling analysis that examines the extent to which students' reports of absences across the two years predict their mathematics and science achievement in Grade 5, after accounting for prior achievement in Grade 4 and other contextual variables. Information on potential causal explanations is beyond the scope of this report; however, the analysis seeks to identify patterns, examine whether these are consistent across participating countries, and inquire into how these may help in understanding associations between continued absences over two years of observation, student achievement and growth, and other student context variables. The report concludes with key takeaways from the analysis, as well as suggestions for future research exploring the relationship between student absence and achievement using TIMSS 2023 Longitudinal data, including alternative analytical approaches and similar analyses of the Grade 8 and 9 data.

Background

The Importance of Student Presence at School

School attendance and student absences are two ways of framing the same phenomenon: students' presence at school. Attendance refers to students being present at school during the academic year,⁵ whereas absences refer to students not being present at school when they are expected to be. School attendance can also be understood more broadly than physical presence alone, as it relates to how students experience school and engage with learning,⁶ including a sense of belonging and relationships with their teachers and students.^{7,8} At its fundamental level, attendance provides opportunities for everyday interactions with teachers and peers in school settings.⁹ These experiences may support students' engagement in learning by helping them participate in lessons and classroom activities. Over time, regular interaction with teachers and peers in a classroom setting can also be associated with the development of academic skills.¹⁰ When students are absent, these opportunities are reduced, making it more challenging for them to keep pace with instruction and participate meaningfully in learning.^{11,12} When attendance is inconsistent, particularly in early grades, students may miss key instructional moments that can strengthen their cognitive skills and lay a foundation for later learning.¹³ As a result, students may feel confused about ongoing classroom tasks or uncertain about expectations, which can further reduce their participation in both academic and social activities at school.¹⁴

Disruptions in learning and participation can be linked to students' sense of belonging in school.^{15,16} Sense of school belonging refers to school connectedness and the extent to which students feel accepted, valued, and connected to others, and to their enjoyment of the school environment.¹⁷ It develops through students' relationships with teachers and peers, where they feel supported and recognized as part of the school community.^{18,19,20} Theories of motivation suggest that this need for connection is a basic psychological need that supports students' engagement and participation in school.^{21,22,23} Negative school experiences, such as bullying, are associated with higher rates of absence, suggesting that negative peer interactions may discourage students from attending school regularly.^{24,25,26} Overall, students who feel less connected to their school environment are more likely to be absent. In contrast, a stronger sense of belonging is associated with greater engagement in school. It is possible that these relationships are reciprocal; absence may decrease a sense of belonging at school, which, in turn, may further reduce motivation to attend.

Attendance and experiences at school can also shape students' perceptions of themselves as learners. Academic self-concept refers to students' perceptions of their own abilities relative to their peers^{27,28} and is shaped by classroom interactions such as participation, feedback, and engagement with learning tasks.^{29,30} As noted above, student presence in the classroom is required for these types of experiences to occur. Specifically in mathematics, some evidence suggests that academic self-concept is associated with student attendance: regular attendance is associated with higher self-concept, and greater absenteeism is associated with lower self-concept.^{31,32} Repeated experiences of difficulty or failure can reduce students' academic self-concept and lead to school withdrawal,³³ suggesting a reciprocal relationship between these processes, similar to what is noted above regarding sense of school belonging.

Socioeconomic status (SES) is also relevant in considering why students' presence at school matters. Students from lower socioeconomic backgrounds are more likely to experience frequent

or chronic absences, particularly in the early grades, for example, due to illness or injury and housing instability.³⁴ For these students, being present at school may be important because schools provide learning resources that may be less available outside of school. Families with more socioeconomic advantages may be better able to make up for those resources when students are not in school.³⁵ This pattern is also reflected in evidence showing that the negative association between absences and literacy development is stronger for lower-SES students than for students from average-SES backgrounds.³⁶ In this sense, regular attendance plays a compensatory role for lower-SES students by providing access to educational resources that can help reduce achievement gaps.³⁷

Overall, evidence suggests that school attendance (and thus student absenteeism) is closely linked to students' experiences in the school environment. Positive relationships with teachers and peers, a sense of belonging, and supportive classroom climates can encourage regular attendance, while negative school experiences may be linked to school avoidance and absences. Socioeconomic status is also relevant in this context, as schools may provide learning resources and support for students from lower SES, who may have fewer resources outside school.^{38,39} These findings highlight that student attendance is not only directly related to students' engagement with learning but also to their broader social and psychological experiences within school.

Student Absenteeism and Academic Achievement

The relationship between school attendance and academic achievement has been widely examined in prior studies, and a substantial body of evidence suggests that student absences are consistently associated with lower levels of academic achievement.^{40,41,42,43,44,45,46} Although many of these studies used longitudinal designs, it is worth noting that they often do not explicitly model student growth over time. To name a few studies that followed students over time, evidence from Sweden suggests that absences in grades 1 and 4 are associated with lower academic achievement within the same grade, including mathematics, reading, speaking, and writing.⁴⁷ Another study following students across the primary school years in England found that students with consistently high or increasing absence rates tend to have lower achievement in mathematics, English, and other subjects, such as science, languages, and history.⁴⁸

In primary school settings, evidence from students followed from kindergarten through fourth grade suggests that the association between absences and achievement becomes stronger as students' progress through the grades.^{49,50,51,52} It can be hypothesized that as students advance through school, instructional content becomes more complex and cumulative, making it more difficult to catch up on missed material. Older students also receive instruction from multiple teachers across subjects, potentially creating further challenges for students attempting to catch up after periods of absence.⁵³

In addition to variation across grades, there is also evidence of differences in the association between absence and achievement across subjects. For example, a study in the United States following students from second through fourth grade found that absences were more strongly associated with lower achievement in mathematics than in reading.⁵⁴ Mathematics knowledge builds cumulatively and relies heavily on direct classroom instruction, which may make it more difficult to recover missed content outside the classroom.^{55,56,57} In contrast, reading and language skills in the early grades may potentially also be developed at home, allowing some students to

partially make up for missed instructional time, depending on learning resources and support available to them.^{58,59}

Prior to the TIMSS 2023 Longitudinal study, research using TIMSS data has also contributed to conversations regarding the relationship between student absences and academic achievement. Because TIMSS has collected information on students' reports of absences across several cycles, a substantial body of secondary research uses TIMSS data to further explore the relationship between school attendance and mathematics and science achievement internationally. Evidence from these studies further supports the negative association between student absenteeism and academic achievement for fourth-grade students.^{60,61,62,63} Analyses of Grade 4 TIMSS data across many countries, including Ireland, Kosovo, North Macedonia, Serbia, and Türkiye, consistently find that students who report more frequent absences tend to show lower achievement in mathematics and science than those who attend school regularly.^{64,65,66} These patterns are consistent with earlier findings highlighting the role of attendance in providing structured learning opportunities and feedback, while absences reduce students' exposure to these processes. The consistency of these findings across different education systems suggests that the relationship between absenteeism and achievement is not limited to national contexts but reflects a broader international pattern.

Overall, findings from studies using TIMSS data are consistent with other research, indicating that higher levels of student absences are associated with lower academic achievement. This highlights the role of regular instructional exposure in supporting learning, particularly in subjects such as mathematics and science that rely on continuous classroom engagement.

Exploring Student-Reported Absence in TIMSS 2023 Longitudinal

This Insights report contributes to the ongoing existing research discussion of how student absences are related to academic achievement. Consistent with the results from discussed above, it was expected that further analysis of the TIMSS 2023 Longitudinal data would reveal negative associations between students' reports of absences from school and their performance in mathematics and science and growth in the subjects between Grades 4 and 5.

Students participating in TIMSS 2023 Longitudinal completed a context questionnaire in both 2023 and 2024 as part of the assessment. Both questionnaire administrations included an item asking students to report how frequently they were absent from school. This questionnaire item is shown in Exhibit 2. As with all student questionnaire data from both time points, this item collected *students' reports* of school absences, not external records of the number of days they were absent in a given academic year. It is possible that students' *actual absences* differ from what they report on the questionnaire at one or both time points. Prior research points to several possible reasons for such discrepancies, including inaccurate recall, social desirability bias, or response styles.^{67,68}

Exhibit 2: Student Absence Item from the Student Questionnaire (Administered in 2023 and 2024)

About how often are you absent from school?*Fill **one** circle only.*

- Once a week -- ☐
- Once every two weeks -- ☐
- Once a month -- ☐
- Once every two months -- ☐
- Never or almost never -- ☐

As discussed in the [TIMSS 2023 Longitudinal International Results](#), students' reports of school absences were negatively associated with student achievement in mathematics and science in both Grades 4 and 5, and with achievement growth in these subjects between the two grades. For both subjects within each assessment year, students who reported higher rates of absence tended to have lower average achievement than those who reported fewer absences. This pattern was consistent across the nine countries. Students who reported more frequent absences in Grade 5 (2024) also tended to show lower average growth in mathematics and science across the countries. The negative associations are more pronounced for students who reported the most frequent absences—those who reported being absent “once a week” or “once every two weeks.” While these groups of students showed the lowest average achievement or growth in mathematics and science across countries, students who reported more occasional absences (i.e., “once every two months,” “once a month”) did not always show lower achievement than students who reported being absent “never or almost never.” This Insights report builds upon these initial findings from the *TIMSS 2023 Longitudinal International Results* by considering students' reports of absences across the two grades concurrently, rather than focusing on relationships within a single school year.

Several exploratory analyses were conducted with the student absence data, building towards the hierarchical linear modeling (HLM) analysis presented later in this report. Exhibit 3 shows migration plots illustrating patterns in students' responses to the absence questionnaire item in Grade 4 (2023) and Grade 5 (2024) across the nine countries. Students' Grade 4 responses are shown on the left side of each plot, and their Grade 5 responses are shown on the right side, with the height of each category corresponding to the proportion of the students. The colored bars moving across the graph illustrate how students' responses to the item changed (or not) between the two assessment years.

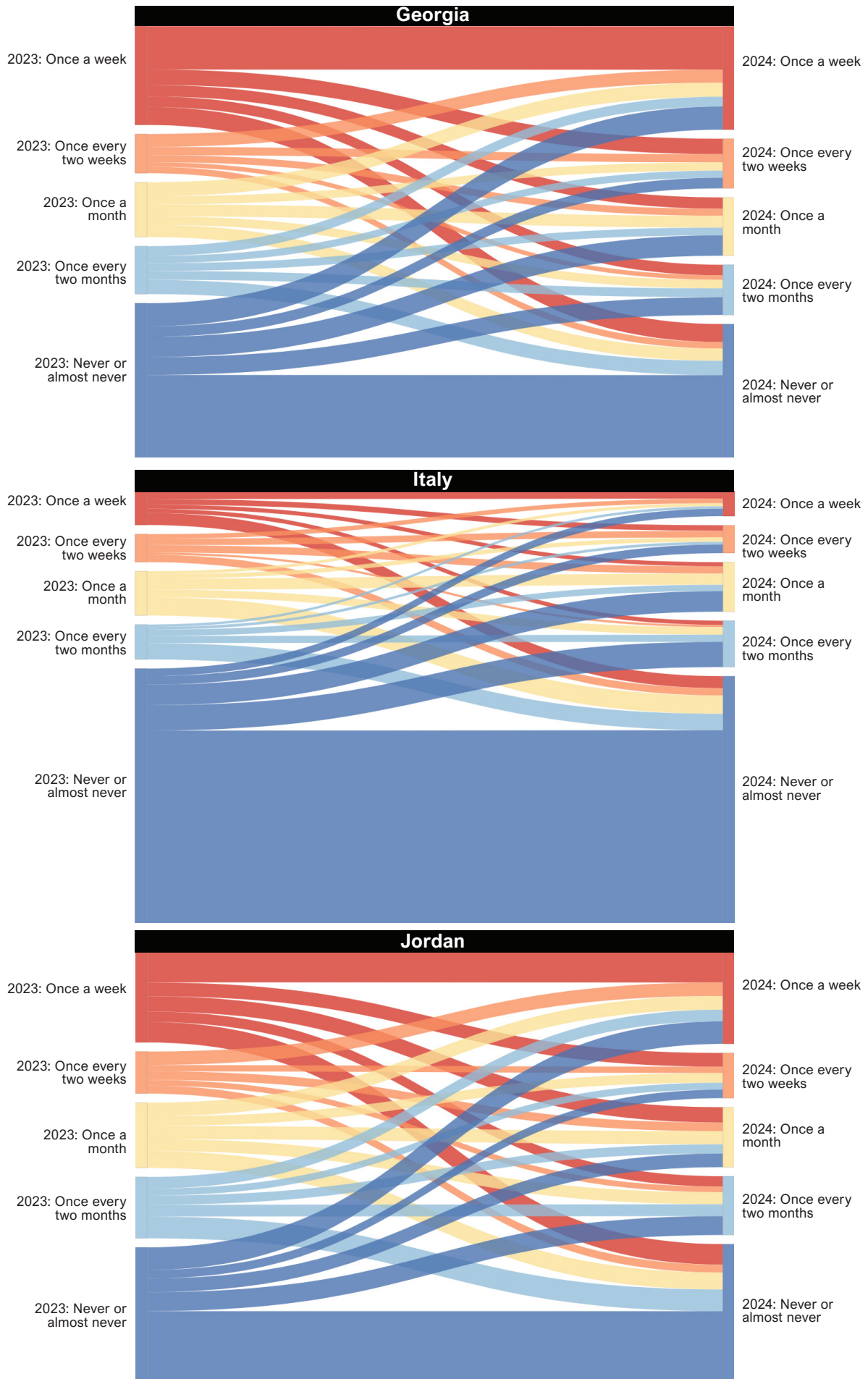
Exhibit 3: Migration Plots of Student Responses to Absence Item in Grades 4 and 5

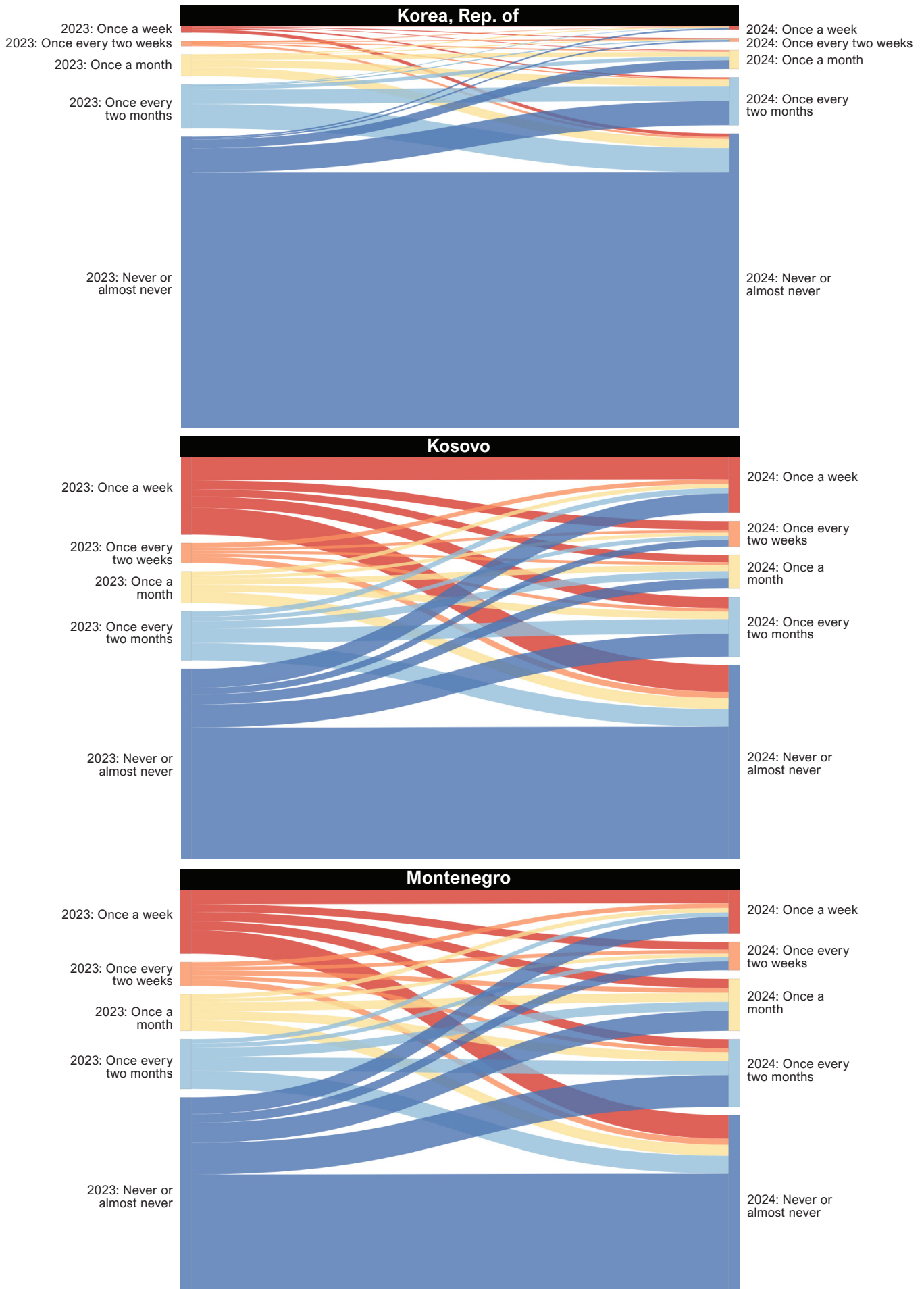
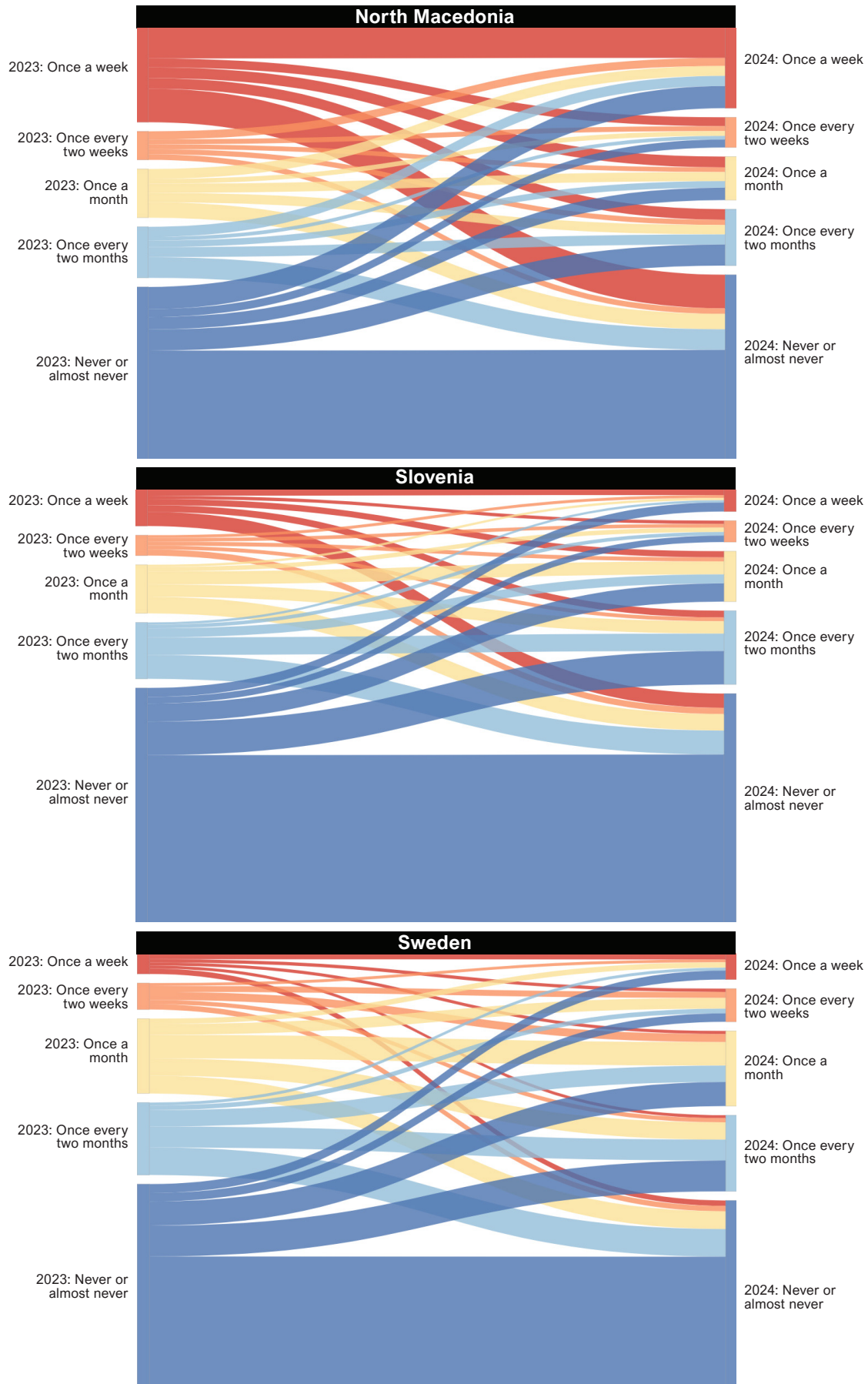
Exhibit 3: Migration Plots of Student Responses to Absence Item in Grades 4 and 5 (Continued)

Exhibit 3: Migration Plots of Student Responses to Absence Item in Grades 4 and 5 (Continued)

Plots were generated using only complete cases who reported on their absences in 2023 and 2024; some students may not have been present for the Grade 5 assessment or may have skipped the absence questionnaire item in one or both assessment years. See [Appendix C](#) for further details about missing data.

In all countries, similar proportions of students selected each response category in both 2023 and 2024, although these were not necessarily the same students in each year. All countries had some students who chose the same response at both time points, and it is worth noting that, in all countries, the largest proportion of students in each year were absent “never or almost never,” and many students who reported being absent “never or almost never” in Grade 4 reported the same in Grade 5. Although some students reported frequent absences (at least once every two weeks) in both years, there are also relatively large groups of students across countries who reported frequent absences in Grade 4 but not in Grade 5, or vice versa. This suggests that students’ reports of frequent absences are not necessarily stable over time and may change between years—either because of real differences in absence rates between the two years or because of the nature of self-reports. Possible reasons include severe or lasting health problems for the student, or a family member, in one year but not the other, or other events that prevented the student from regular attendance in just one of the two years. Students provided this data based on their own recollections, so some variability is expected between years. There also may be different reasons why absences vary from year to year beyond those discussed in this report.

Based on this exploratory work, as well as findings in the *TIMSS 2023 Longitudinal International Results* related to student absences, the original response categories for the absence item were recoded for further analysis to create four distinct groups of students based on data from both years: 1) rare absence in both years; 2) frequent absence in 2023 and rare absence in 2024; 3) rare absence in 2023 and frequent absence in 2024; and 4) frequent absence in both years. These groups are described in Exhibit 4.

Exhibit 4: Student Absence Classifications Using 2023 and 2024 Responses

Absence Classification	Explanation
Rare Absence in Both Years	<i>Student response in 2023</i> • Never or almost never OR • Once every two months OR • Once a month <i>Student response in 2024</i> • Never or almost never OR • Once every two months OR • Once a month
Frequent Absence in Grade 4 (2023) / Rare Absence in Grade 5 (2024)	<i>Student response in 2023</i> • Once a week OR • Once every two weeks <i>Student response in 2024</i> • Never or almost never OR • Once every two months OR • Once a month
Rare Absence in Grade 4 (2023) / Frequent Absence in Grade 5 (2024)	<i>Student response in 2023</i> • Never or almost never OR • Once every two months OR • Once a month <i>Student response in 2024</i> • Once a week OR • Once every two weeks
Frequent Absence in Both Years	<i>Student response in 2023</i> • Once a week OR • Once every two weeks <i>Student response in 2024</i> • Once a week OR • Once every two weeks

Exhibit 5 shows the percentages of students within each country that were in each absenteeism classification, along with their average mathematics achievement in each assessment year. For all nine countries, the largest percentage of students were absent rarely in both assessment years. Korea had the highest percentage of students in this category (95%), indicating that the vast majority reported seldom being absent in either Grade 4 or 5. Only two countries (Georgia and Jordan) had fewer than 50 percent of students in this category (47% and 48%, respectively). Along with the migration plots, this provides evidence that regular school attendance across both time points is the norm for many students in the TIMSS 2023 Longitudinal countries; however, country-level variations in this pattern warrant further investigation.

Exhibit 5: Student Absence Classifications and Average Mathematics Achievement in Grades 4 and 5

Country	Rare Absence in Both Years			Frequent Absence in 2023 / Rare Absence in 2024			Rare Absence in 2023 / Frequent Absence in 2024			Frequent Absence in Both Years		
	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)
Georgia	r 47 (1.2)	522 (3.6)	546 (3.5)	15 (0.7)	472 (5.8)	499 (6.4)	18 (1.0)	485 (5.5)	499 (5.8)	20 (0.9)	474 (4.3)	492 (4.7)
Italy	77 (0.8)	524 (2.7)	563 (2.6)	9 (0.5)	486 (4.9)	525 (5.5)	7 (0.5)	499 (6.4)	533 (7.1)	6 (0.5)	484 (7.2)	519 (6.1)
Jordan	r 48 (1.3)	448 (6.1)	462 (5.4)	17 (0.9)	410 (6.9)	420 (6.4)	18 (1.1)	422 (8.7)	423 (7.6)	16 (1.1)	398 (7.3)	410 (6.1)
Korea, Rep. of	r 95 (0.5)	597 (2.4)	638 (2.4)	2~	~~	~~	1~	~~	~~	1~	~~	~~
Kosovo	r 62 (1.3)	469 (3.4)	487 (3.6)	16 (0.8)	434 (4.5)	453 (5.1)	11 (0.7)	424 (5.2)	435 (6.4)	11 (0.7)	409 (8.0)	425 (7.3)
Montenegro	r 65 (0.8)	492 (2.1)	512 (1.7)	15 (0.6)	452 (3.9)	476 (3.5)	11 (0.5)	456 (4.5)	464 (4.4)	8 (0.4)	435 (4.9)	450 (4.6)
North Macedonia	r 54 (1.1)	497 (3.4)	519 (3.2)	18 (0.9)	463 (4.7)	479 (5.2)	15 (0.8)	453 (6.3)	456 (5.4)	13 (0.7)	435 (5.4)	439 (6.5)
Slovenia	r 78 (0.7)	525 (1.9)	568 (2.0)	10 (0.5)	483 (4.3)	529 (4.4)	7 (0.5)	494 (4.5)	533 (5.2)	4 (0.3)	471 (7.4)	514 (6.6)
Sweden	r 78 (1.1)	542 (2.8)	572 (2.7)	7 (0.5)	496 (7.1)	533 (7.7)	10 (0.7)	506 (5.9)	529 (7.2)	5 (0.4)	495 (6.7)	521 (7.4)

Standard errors appear in parentheses (). Because of rounding some results may appear inconsistent.

A tilde (~) indicates insufficient data to report result.

An “r” indicates data are available for at least 70% but less than 85% of students.

Much smaller percentages of students were classified as being frequently absent in both assessment years, ranging from 1 percent (Korea) to 20 percent (Georgia). This provides evidence that relatively few students across the TIMSS 2023 Longitudinal countries report persistent attendance problems across time.^a Reports of frequent absence in one year and rare absence in the other are more common than reports of frequent absence in both years in most countries. Across countries, there is no consistent pattern of students reporting more frequent absences in Grade 4 (2023) than in Grade 5 (2024), or vice versa.

The achievement results presented in Exhibit 5 are in line with prior research on student absences and academic achievement. Students who reported rarely being absent in both assessment years showed the highest average mathematics achievement at both time points across all countries. Students who reported frequent absences in both assessment years often showed the lowest average mathematics achievement at both time points. In general, students who reported more frequent absences within a given year typically had lower average mathematics achievement than those who did not report frequent absences in that year. On average, students in all four absence classifications showed at least a small increase in average mathematics achievement between Grades 4 and 5; however, there are likely students of varying

^a It is possible that students may have been absent on one of the assessment days, in which case their data is missing for one time point and is not reflected in these analyses. See [Appendix C](#) for more information about missing data.

trajectories (achievement growth between grades, little achievement change between grades, or achievement decrease between grades) in all four absence classifications across the countries.

Exhibit 6 presents the same percentages of students across the absence classifications, but with average achievement in science for both grades. The results are similar to mathematics—in most cases, students who reported rare absences in both years showed higher average science achievement at both time points, and those who reported frequent absences in both years often showed lower average science achievement. On average, students across the four absence classifications showed at least the same average achievement in science across the two time points—however, as in mathematics, there are likely students of varying trajectories within each classification.

Exhibit 6: Student Absence Classifications and Average Science Achievement in Grades 4 and 5

Country	Rare Absence in Both Years			Frequent Absence in 2023 / Rare Absence in 2024			Rare Absence in 2023 / Frequent Absence in 2024			Frequent Absence in Both Years		
	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)	Percent of Students	Average Achievement (Grade 4)	Average Achievement (Grade 5)
Georgia	r 47 (1.2)	484 (3.4)	510 (3.9)	15 (0.7)	447 (4.8)	470 (5.7)	18 (1.0)	455 (5.8)	469 (5.7)	20 (0.9)	445 (4.5)	463 (3.9)
Italy	77 (0.8)	521 (2.3)	553 (2.6)	9 (0.5)	485 (4.6)	519 (4.4)	7 (0.5)	487 (6.2)	518 (8.2)	6 (0.5)	480 (6.6)	516 (5.9)
Jordan	r 48 (1.3)	441 (5.3)	461 (6.0)	17 (0.9)	394 (6.5)	417 (6.1)	18 (1.1)	409 (8.9)	416 (8.1)	16 (1.1)	385 (7.2)	413 (7.4)
Korea, Rep. of	r 95 (0.5)	585 (2.2)	620 (1.9)	2~	~~	~~	1~	~~	~~	1~	~~	~~
Kosovo	r 62 (1.3)	421 (3.4)	442 (3.5)	16 (0.8)	389 (4.1)	409 (4.2)	11 (0.7)	388 (5.2)	396 (5.7)	11 (0.7)	369 (6.7)	384 (6.1)
Montenegro	r 65 (0.8)	479 (2.0)	498 (1.9)	15 (0.6)	437 (3.7)	460 (3.9)	11 (0.5)	437 (3.7)	448 (4.2)	8 (0.4)	419 (5.0)	433 (5.2)
North Macedonia	r 54 (1.1)	464 (3.5)	477 (3.3)	18 (0.9)	427 (5.3)	440 (5.1)	15 (0.8)	419 (6.0)	419 (5.2)	13 (0.7)	393 (5.3)	401 (5.6)
Slovenia	r 78 (0.7)	538 (1.9)	577 (1.8)	10 (0.5)	492 (4.8)	532 (4.2)	7 (0.5)	506 (5.1)	538 (5.0)	4 (0.3)	479 (8.5)	517 (7.4)
Sweden	r 78 (1.1)	544 (3.3)	573 (3.0)	7 (0.5)	497 (7.8)	533 (8.7)	10 (0.7)	508 (7.4)	534 (8.0)	5 (0.4)	492 (8.4)	520 (8.8)

Standard errors appear in parentheses (). Because of rounding some results may appear inconsistent.

A tilde (~) indicates insufficient data to report result.

An “r” indicates data are available for at least 70% but less than 85% of students.

These initial results provide a descriptive basis for examining how students’ reports of school absences shift between the two data-collection time points in TIMSS 2023 Longitudinal. The following section extends this analysis by using the “frequent” and “rare” absence classifications as predictors in a multilevel modeling framework to explore the relationship between students’ reports of absenteeism in the two years and their mathematics and science achievement.

Using Student-Reported Absence to Predict Achievement in Mathematics and Science

Following the descriptive analyses above, this section presents the results of a hierarchical linear modeling analysis using the student absence classifications as the predictor of interest. Specifically, a series of HLMs were estimated to examine variance in Grade 5 (2024) achievement explained by student absences and other contextual predictors, after controlling for Grade 4 (2023) achievement. Following a general description of the analysis procedures, results are presented with a special focus on the student absence variables. Descriptions of all contextual variables included in the analysis are provided in [Appendix B](#), and further technical details are available in [Appendix C](#).

Hierarchical Linear Models

Hierarchical linear models (HLMs) are regression models designed to analyze hierarchical or nested data structures, such as the data collected in TIMSS, where students are nested within classrooms within schools. HLMs allow for the analysis of data while accounting for school and/or classroom differences, examining how achievement and absenteeism are related at the student, school, and classroom levels. In the context of student absences, some schools may have higher absenteeism than others, which may affect achievement; the relationships we observe may not be solely due to student-level differences, since schools may differ in how they manage absent students.

The HLM models avoid conflating the within-school effect of absenteeism on achievement (students who are absent more often than their peers have lower achievement) with a potentially different between-school effect (e.g., if schools with higher proportions of frequent absenteeism perform better, on average). While this may be an unlikely result for absences, it is well known that country-level and school-level associations can be very different from student-level associations between achievement-related variables such as attitudes or other self-reports. Such conflation can distort substantive interpretation and may lead to the ecological fallacy, whereby researchers draw incorrect conclusions about individual-level relationships from group-level patterns.^{69,70,71}

A key advantage of HLMs is their capacity to partition total variance into distinct within- and between-cluster components, thereby providing coefficients that quantify the relative importance of each level in the analysis.^{72,73,74} These coefficients enable the identification of the relative contributions of individual factors, such as students' prior-year achievement, self-confidence, or socioeconomic status, and school- or class-level factors, such as aspects of school climate, to predicting student outcomes. These models are essential for distinguishing between individual-level and cluster-level (school) effects, ensuring that school-level influences are not confounded with individual-level processes.

This report uses HLMs with students nested within schools, to focus on the relationship between student-level variables, specifically absenteeism and Grade 5 achievement, while accounting for both student-level characteristics (level-1 fixed effects) and the school-level source of variation (random intercept). Student-level predictors were centered within schools to isolate within-school relationships and to prevent the estimation of parameters that conflate within- and between-school differences. With this approach, coefficients reflect comparisons among students within the same school, such as whether students who reported higher rates of absenteeism than their peers tended to achieve lower scores. By centering within schools and including a school random intercept, the models estimate individual-level associations while accounting for school-level influences not explicitly modeled. The strength of this approach lies in the fact that the potential addition of school-level variables (as discussed in the Future Directions section of this report) would provide information about school-level variables' impact on achievement, but the student-level parameter estimates would not change because within-school centering makes them orthogonal to school-level covariates. This approach reduces the risk of ecological fallacy and provides more interpretable cross-national comparisons of the impact of absenteeism on achievement.

HLM Model Building

To evaluate the associations between absenteeism and students' achievement, three HLMs, with students (level 1) nested within schools (level 2), were estimated. The outcomes of interest were Grade 5 (2024) mathematics and science achievement scores (analyzed in separate models), and the focal predictor was student reports of absenteeism, as discussed in the previous section. The models are summarized in Exhibit 7.

Exhibit 7: Summary of Models

Model	Predictor Variables Included
1. Prior Achievement Only Model	Grade 4 achievement
2. Absenteeism Only Model	Grade 4 achievement + absenteeism
3. Full Model	Grade 4 achievement + absenteeism + home socioeconomic status + bullying + sense of belonging + confidence in subject area + instructional clarity in subject area

All models were estimated separately for each education system to account for differences in national contexts. The stepwise model-building approach in this report sought to explore the associations between absenteeism and Grade 5 achievement, above and beyond the influence of prior-year achievement (Prior Achievement Only Model). Similarly, the Full Model allows for evaluating whether the associations between absenteeism and Grade 5 achievement persist after controlling for other empirically and conceptually relevant student-level covariates.

In the first model (Prior Achievement Only), Grade 5 achievement was predicted solely by prior (Grade 4) achievement, capitalizing on the longitudinal data structure and explaining only between-student variability in Grade 5 achievement. This model serves as the baseline for variance decomposition comparisons in this report; however, it is not a true null, unconditional model. This choice is in line with the analysis goals, which were not simply to partition variance, but to determine whether student reports of absenteeism explain differences in Grade 5 achievement above and beyond students' pre-existing achievement levels. Given the stability of academic achievement over time, controlling for prior achievement as a baseline comparison provides a substantively meaningful reference point for this purpose.

The second model (Absenteeism Only) was estimated to include the main predictor of interest, student-reported absenteeism, in addition to prior achievement. Lastly, a third model (Full Model) was estimated to include conceptually and empirically relevant student-level variables that are correlated with achievement, including parent-reported home socioeconomic status (SES) and student-reported frequency of bullying experiences, sense of school belonging, instructional clarity in mathematics or science lessons, and confidence in mathematics or science (see [Appendix B](#)). The inclusion of covariates helps partial out differences in students' psychosocial factors and school characteristics that might otherwise be confounded with absenteeism. Model predictors were centered within schools and all predictors, except prior achievement and SES, were included in the model as dummy variables. Under school-mean centering, the dummy-coded parameter refers to the average difference in the outcome between the reference group (i.e., Rare Absence in Both Years) and the focal group (e.g., Frequent Absence in Both Years) within clusters, relative to that school's average predictor rate, with other variables in the model held

constant. All the models included a school-level random intercept to account for between-school differences in Grade 5 achievement. With this approach, the school random intercept captures systematic differences among schools (e.g., resources, leadership, efforts to reduce absenteeism, peer context) that are not explicitly captured by the student-level predictors.^b For details on the recoding scheme, sample distribution of predictors, and variable centering, see [Appendix C](#).

Because some students in the longitudinal dataset were present at school and assessed at only one of the two time points,⁷⁵ there was missing data for the cross-year context variables. Missing data in context variables were addressed using multilevel multiple imputation by chained equations (MICE)^{76,77} within a fully conditional specification (FCS) framework.^{78,79} Details on HLM final model formalization, complete-case intraclass correlation estimates, imputation, and parameter pooling can be found in [Appendix C](#).

The investigation was designed to enable systematic comparison of absence–achievement relationships across the nine participating education systems. Central to the analysis was the quantification of explained variance in Grade 5 achievement, with particular attention to the incremental predictive contribution of student absence classifications beyond prior achievement and other covariates. The primary analytic interest lay in the consistency and comparability of predictor effects—especially those of the four absence groups—across countries. Variance estimates were derived to quantify the uncertainty attributable to multiplying imputed background data, thereby providing a more complete accounting of the variability inherent in the analysis. Statistical significance testing was not undertaken; interpretation instead rests on the magnitude, direction, and cross-national convergence of the estimated coefficients.^c

HLM Results

Variance Decomposition

The HLM variance components were evaluated to identify additional variability in Grade 5 achievement that is explained by including the absenteeism predictors and other relevant student characteristics, beyond that already explained by prior-year achievement. The purpose was to further contextualize findings on student reports of absenteeism and their relationship to mathematics and science achievement growth, defined as Grade 5 achievement once the prior year’s achievement is controlled for. Exhibits 8 and 9 show the variance decomposition for the three estimated models (Prior Achievement Only, Absenteeism Only, Full Model) for mathematics and science growth, respectively. Given that all student-level predictors were centered within schools, the estimated parameters and the associated reductions in unexplained variance reflect within-school differences among students, beyond differences between schools. Furthermore, because school-level (level-2) covariates were not included in any model, changes in the variance components across models are interpreted as the extent to which within-school student characteristics explain remaining variation in achievement, while between-school variation

^b Between-school variation is not the focus of the present report, but it might be of interest to researchers. For reference, conditional intraclass correlations from complete-case on student reports of absenteeism and their relationship to HLMs are provided in [Appendix C](#).

^c In large samples such as those obtained from international largescale assessments, conventional significance tests may provide limited useful information. As Kish (1965) observed, statistical significance testing is not appropriate for research using large scale survey data: Referring to Yates (1951), Kish concludes “If the sample is large enough, the weakest and least significant relationships will appear ‘statistically significant’ if tested.” More recently, Lin, Lucas, and Shmueli (2013) demonstrated that p-values become systematically deflated with large sample sizes, leading to statistically significant results even for substantively negligible effects. Amrhein, Greenland, and McShane (2019), along with over 800 signatories, called for retiring statistical significance altogether, arguing that dichotomous thresholds distort interpretation and discourage uncertainty quantification. The present analysis therefore focuses on effect magnitudes, explained variance, and cross-national comparability, following the recommendation of Wasserstein, Schirm, and Lazar (2019) to move beyond a simple “ $p < 0.05$ ” paradigm.

is captured as unexplained school-level variance through random intercepts; no school-level predictors are included to account for it. Therefore, the results presented focus on evaluating the incremental contribution of student-level variables (absenteeism, then student experiences and characteristics) based on changes in the level-1 variance estimates.

Mathematics Achievement Models

Exhibit 8 shows the variance decomposition for the mathematics models. Here, σ (sigma) represents the within-group residual standard deviation—the typical amount that individual observations deviate from their group’s predicted value after accounting for the fixed effects; τ (tau) is the between-group random intercept (or slope) variance, capturing how much groups vary around the overall fixed effect. Together with the reported R^2 -squared percentage change values (e.g., marginal and conditional), σ and τ help decompose unexplained variance: smaller σ indicates better level-1 fit, while small τ would suggest little remaining heterogeneity across clusters if level-2 predictors were to be included.

The results in Exhibit 8 show that, as expected, the largest increases in explained level-1 variance occur when adding other relevant student-level variables, such as home SES, alongside student-reported variables related to school experiences. Full model variance components show that, beyond prior-year achievement and absenteeism predictors, the broader set of student background and experience variables account for additional within-school differences in achievement, producing a larger increase in explained variance, expressed as level-1 R^2 increase, than absenteeism alone, even though substantial within-school heterogeneity remains. The largest increases in R^2 were observed in Montenegro, North Macedonia, and Sweden, with increases of 7.71 percent, 5.76 percent, and 5.09 percent in level-1 R^2 , respectively, relative to Model 1 (Prior Achievement + Absence). Looking only at “model 1”, it is important to keep in mind that higher levels of absences are more broadly seen in those countries where the inclusion of absences increases R^2 —for example, Georgia, where about 20 percent of students report frequent absences in both years and the R^2 increase is largest among countries.

Lastly, the exhibit shows moderate intraclass correlations (ICCs), ranging from 0.21 to 0.55, with virtually no change across models and participating education systems. This is consistent with how the models were specified (school-centered predictors and no school-level covariates). Given all student-level variables are centered within schools (and therefore are orthogonal to school-level variability), their inclusion in the models reduced level-1 variance without affecting between-school (level-2) variance, resulting in minimal changes to ICC values across different model specifications.

Exhibit 8: Variance Decomposition – Mathematics

Country	Baseline Model (Prior Achievement Only)			Model 1 (Prior Achievement + Absence)				Full Model (All Predictors)			
	Sigma	Tau	ICC	Sigma	Tau	ICC	Level 1 R ² % Change	Sigma	Tau	ICC	Level 1 R ² % Change
Georgia	2422.73	2868.20	0.54	2389.94	2873.06	0.55	1.35	2316.25	2879.86	0.55	3.08
Italy	1922.49	1931.74	0.50	1915.42	1932.39	0.50	0.37	1824.07	1929.03	0.51	4.77
Jordan	3947.04	4606.91	0.54	3913.07	4607.20	0.54	0.86	3769.18	4607.86	0.55	3.68
Korea, Rep. of	1441.23	1151.72	0.45	1437.31	1152.43	0.45	0.27	1416.41	1154.13	0.45	1.45
Kosovo	2293.77	2589.20	0.53	2272.10	2590.97	0.53	0.94	2180.76	2592.53	0.54	4.02
Montenegro	2739.67	1144.65	0.29	2697.39	1150.18	0.30	1.54	2489.40	1170.60	0.32	7.71
North Macedonia	3448.59	2437.07	0.41	3359.81	2440.34	0.42	2.57	3166.29	2435.04	0.43	5.76
Slovenia	1703.87	449.95	0.21	1698.60	450.14	0.21	0.31	1638.28	450.28	0.22	3.55
Sweden	1686.75	1163.36	0.41	1681.24	1163.80	0.41	0.33	1595.61	1154.61	0.42	5.09

Level 1 R² change relative to prior model.

Variance estimates averaged across 10 imputations and 5 plausible values for each education system.

Science Achievement Models

Exhibit 9 presents the variance decomposition for the three models estimated for science. Science models' variance components yielded very similar results to those from mathematics achievement models. Specifically, results show that adding absenteeism indicators to the Prior Achievement Only model produced only relatively small reductions in the level-1 variance across education systems. The latter indicates that absenteeism accounts for a modest share of the remaining within-school variability, even after controlling for prior-year science achievement. Consistent with these small shifts in level-1 variance explained, level-1 R² increments ranged from 0.11 percent in Italy to 2.34 percent in North Macedonia. As expected, the largest reductions in level-1 variance once again occurred when adding the broader set of student-level covariates (home SES, student-reported bullying experiences, sense of school belonging, instructional clarity in science lessons, and confidence in science). The Full Model variance components show that, beyond prior-year achievement and absenteeism, additional student background and experiences yielded larger incremental level-1 R² gains than absenteeism alone in every system. The largest increases in level-1 R² at this step were observed in Georgia (6.29%), Montenegro (6.27%), and North Macedonia (4.91%). More modest increases were observed in Italy (3.15%), Jordan (3.09%), Slovenia (3.03%), Sweden (2.92%), and the Republic of Korea (2.16%). As with mathematics achievement models, intraclass correlations (ICCs) remained stable all models, ranging from 0.21 to 0.61, with virtually no change across model specifications. Again, the stability is expected and consistent with modeling choices, indicating that a large proportion of the remaining unexplained variability in Grade 5 science achievement growth lies between schools, even after accounting for prior achievement and multiple within-school student characteristics.

Exhibit 9: Variance Decomposition – Science

Country	Baseline Model (Prior Achievement Only)			Model 1 (Prior Achievement + Absence)				Full Model (All Predictors)			
	Sigma	Tau	ICC	Sigma	Tau	ICC	Level 1 R ² % Change	Sigma	Tau	ICC	Level 1 R ² % Change
Georgia	2170.08	3037.79	0.58	2133.55	3044.10	0.59	1.68	1999.44	3059.31	0.61	6.29
Italy	1541.02	1521.26	0.50	1539.31	1521.47	0.50	0.11	1490.86	1515.10	0.51	3.15
Jordan	3990.94	4441.75	0.53	3973.62	4442.96	0.53	0.43	3850.92	4442.11	0.54	3.09
Korea, Rep. of	1403.77	1036.59	0.43	1400.70	1037.16	0.43	0.22	1370.41	1039.83	0.44	2.16
Kosovo	2221.03	1914.33	0.46	2173.26	1917.25	0.47	2.15	2085.28	1916.71	0.48	4.05
Montenegro	2608.58	1376.03	0.35	2570.38	1383.11	0.35	1.46	2409.31	1405.30	0.37	6.27
North Macedonia	2981.87	2520.99	0.46	2912.21	2523.61	0.46	2.34	2769.32	2517.09	0.48	4.91
Slovenia	1656.25	446.60	0.21	1639.53	447.14	0.22	1.01	1589.79	447.09	0.22	3.03
Sweden	2034.65	1565.91	0.44	2024.82	1566.83	0.44	0.48	1965.76	1549.03	0.44	2.92

Level 1 R² change relative to prior model.

Variance estimates averaged across 10 imputations and 5 plausible values for each education system.

Model 1: Absenteeism Only

The proportions of explained variance in achievement growth at the school and student levels indicate the relative importance of selected predictors in modeling Grade 5 achievement, controlling for Grade 4 achievement. As a next step, HLM model results are presented here, focusing on regression parameter patterns across the nine countries, including the magnitude and consistency of their direction. Evidence of consistent results across different country contexts is taken as evidence of the stability of the relationship between absences and achievement.

Mathematics Achievement

Exhibit 10 shows the Absenteeism Only model results for mathematics, highlighting the negative impact of frequent absenteeism on achievement growth in mathematics across all nine education systems.

Results show that after controlling for prior mathematics achievement, reports of frequent absenteeism in Grade 4 only (the year prior to the assessment) were consistently associated with lower mathematics achievement. The negative association ranged from 1.07 points in Sweden to 12.31 points in North Macedonia, meaning that students who reported frequent absenteeism in the year prior to the assessment scored, on average, between approximately 1 and 12 points lower than peers in the same school who were rarely absent in both years, controlling for prior mathematics achievement. The consistency of negative coefficients across countries provides evidence that, even when absenteeism occurred only in the year prior to the assessment, students who were frequently absent scored, on average, lower than peers in the same school who reported rare absences in both school years. That said, the magnitude of these negative associations varies across the participating countries.

Exhibit 10: Selected HLM Results, Impact of Frequent Absenteeism on Grade 5 (2024) Mathematics Achievement (Model 1, Absenteeism Only)

Country	Intercept		Grade 4 (2023) Mathematics Achievement		Frequent Absence, 2023 Only		Frequent Absence, 2024 Only		Frequent Absence in Both Years	
	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *
Georgia	519.68	7.17	0.79	0.03	-8.76	3.62	-10.02	3.02	-14.62	3.32
Italy	549.36	5.17	0.82	0.02	-3.99	3.93	-5.02	3.41	-8.88	4.45
Jordan	454.48	8.05	0.66	0.02	-8.03	4.02	-11.11	3.99	-15.53	3.80
Korea, Rep. of	624.86	5.33	0.86	0.03	-5.83	6.11	-10.15	7.20	-13.14	10.88
Kosovo	451.70	6.65	0.81	0.03	-4.71	3.52	-11.92	4.53	-11.48	3.86
Montenegro	492.56	3.19	0.75	0.03	-4.61	3.01	-17.06	3.12	-17.30	3.45
North Macedonia	489.46	4.98	0.71	0.03	-12.31	3.44	-22.27	3.67	-24.11	4.45
Slovenia	553.33	2.16	0.84	0.03	-3.94	2.79	-6.60	3.16	-6.40	3.95
Sweden	559.65	3.38	0.84	0.04	-1.07	3.62	-6.50	3.01	-6.37	4.17

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system. See Estimates Pooling in [Appendix C](#) for further details.

The magnitude of regression coefficients for prior achievement is not directly comparable to those for the absenteeism variables because prior achievement is measured on a different scale.

See Exhibit C.8 for full model parameter estimates.

Student-reported absences in Grade 5 (2024, the assessment year) were consistently more detrimental than in the year prior to the assessment, as evidenced by larger negative coefficients across all education systems. The negative associations between reports of frequent Grade 5 absenteeism and Grade 5 mathematics achievement ranged from 6.50 in Sweden to 22.27 in North Macedonia. This means that students who reported being frequently absent only in Grade 5 showed mathematics achievement scores that were, on average, between approximately 6 and 22 points lower than peers in the same school who reported rare absences in both years. In some countries (e.g., Kosovo, Montenegro, North Macedonia, Slovenia), this negative association was two to four times larger than that found for students reporting frequent absenteeism in the year prior to the assessment. This consistent pattern across countries provides evidence that frequent absence during the assessment year is more strongly associated with lower growth in mathematics achievement than frequent absence during the previous year.

Lastly, the largest negative associations between absenteeism and Grade 5 mathematics achievement were observed among students who reported frequent absences in both years across six of the nine participating education systems. In these education systems, students who reported being frequently absent in both years showed Grade 5 mathematics achievement score gains that are, on average, between 8.88 (Italy) and 24.10 (North Macedonia) points lower than peers in the same school who reported rare absences in both years. It is worth noting that this group is very small in some countries (e.g., Korea), leading to increased uncertainty about the coefficient estimate.^d Even in the three systems where absenteeism in both years did not show the *largest* negative association (Kosovo, Slovenia, and Sweden), a robust relationship was still observed between student reports of frequent absences in both years and Grade 5 mathematics achievement gains. This suggests there is potential for compounded effects of persistent absenteeism across multiple school years, while absences in prior years can be overcome to some extent.

These results show a consistent pattern across almost all education systems: Students who reported frequent absences from school in either assessment year had lower achievement

^d See Exhibit C.2 for details on sample distributions of predictors.

than those who reported rare absences in both years. More recent absences appear to be more detrimental to mathematics achievement, as students who were frequently absent only in 2024 scored lower, on average, than those who were frequently absent only in 2023. Students who were frequently absent in both years also scored lower, on average, than peers who reported rare absences in both years, and scored the lowest in six out of the nine participating systems. This provides strong, coherent evidence: Both the timing and the persistence of absenteeism matter for mathematics achievement.

Science Achievement

Exhibit 11 shows the same selection of Absenteeism Only model results for science achievement. As for the mathematics models, the results highlight the negative impact of frequent absenteeism on Grade 5 science achievement across all nine education systems.

After accounting for prior science achievement, student reports of absenteeism were generally associated with lower Grade 5 science achievement in all countries. For students who reported frequent absences only in Grade 4, the largest negative associations were observed in Georgia and Kosovo, where, on average, students who reported being frequently absent only in Grade 4 scored 9.19 and 8.75 points lower, respectively, than their peers in the same schools who reported rare absences in both years. It is worth noting that in the case of Korea, the uncertainty of the estimate (i.e., a large standard error) is due to the small number of cases in this absenteeism category. However, that is not necessarily the case for Montenegro and Sweden (see Exhibit C.2 for the sample distribution of predictors).

**Exhibit 11: Selected HLM Results, Impact of Frequent Absenteeism on Grade 5 (2024)
Science Achievement (Model 1, Absenteeism Only)**

Country	Intercept		Grade 4 (2023) Science Achievement		Frequent Absence, 2023 Only		Frequent Absence, 2024 Only		Frequent Absence in Both Years	
	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *	Estimate	S.E. *
Georgia	491.17	7.70	0.79	0.04	-9.19	4.16	-12.33	3.49	-14.26	3.00
Italy	541.30	4.50	0.79	0.03	-2.89	2.82	-2.14	4.36	-0.29	3.73
Jordan	450.89	7.71	0.73	0.04	-7.68	3.76	-9.30	4.18	-8.17	4.37
Korea, Rep. of	617.55	5.35	0.84	0.04	-4.04	7.41	-10.07	7.50	-8.51	11.18
Kosovo	410.93	5.36	0.74	0.05	-8.75	3.63	-17.40	3.89	-16.98	3.75
Montenegro	480.20	3.49	0.77	0.04	-4.26	3.08	-15.81	2.90	-17.07	3.50
North Macedonia	451.70	5.14	0.68	0.04	-7.74	2.89	-20.73	3.51	-20.78	3.91
Slovenia	561.31	2.18	0.77	0.03	-6.22	2.70	-12.35	3.32	-12.39	4.88
Sweden	560.10	3.87	0.79	0.05	-5.03	5.20	-8.13	3.17	-8.15	4.38

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system. See Estimates Pooling in [Appendix C](#) for further details.

The magnitude of regression coefficients for prior achievement is not directly comparable to those for the absenteeism variables because prior achievement is measured on a different scale.

See Exhibit C.9 for full model parameter estimates.

Similar to mathematics, reports of frequent absenteeism only in Grade 5 appear to be more detrimental than those only in Grade 4, with notably larger negative associations in eight out of the nine education systems.^e Some of the most notable examples are North Macedonia, Kosovo, and Montenegro, where students who reported being frequently absent only in Grade 5 showed science achievement growth that is, on average, around 20.73, 17.40, and 15.81 points lower

^e In Italy, the regression coefficients for frequent absences in Grade 4 only and Grade 5 only were very similar.

than peers who reported rare absences in both years. Students who reported absence in 2023 (Grade 4) in comparison, showed, on average, lower growth amounting to 7.74, 8.75, and 4.26 points. This suggests that students with frequent absences in prior years can, to some extent, catch up in subsequent years, whereas absences in the current year (either consistent over both years or only in the 2024 school year) are associated with substantially lower growth.

Lastly, reports of persistent absenteeism (e.g., frequent absence in both years) were associated with lower Grade 5 science achievement in all countries. The category showed the largest negative impacts on science achievement in five of nine education systems, ranging from 12.39 in Slovenia to 20.78 in North Macedonia. However, the differences in negative coefficients for students who reported absences in both years and those who reported absences only in Grade 5 are all quite small.

Model 2 (Full Model)

Several empirically and conceptually relevant student-level covariates were added to the final model with the intention of partialling out differences in students' experiences and characteristics that might otherwise be confounded with absenteeism. These covariates are parent-reported home socioeconomic status (SES) and student-reported frequency of bullying experiences, sense of school belonging, instructional clarity in mathematics or science lessons, and confidence in mathematics or science. Relative to the previous Absenteeism Only model, these additional covariates increased the level-1 explained variance, expressed as R^2 increase, between 1.45 and 7.71 percent in the mathematics models and between 2.16 and 6.29% in the science models. Selected parameters from these models are presented in the following sections—specifically, the regression coefficients for prior achievement, home socioeconomic status, and the absenteeism variables. Full results including parameters for all covariates are presented in Exhibits C.8 and C.9.

Mathematics Achievement

The negative associations between absenteeism and mathematics achievement observed in the Absenteeism Only model remain across eight out of nine countries in the Full Model,^f but the magnitude decreases after the inclusion of covariates that are also associated with achievement gains (see Exhibit 12). These negative coefficients ranged from 2.70 in Kosovo and Montenegro to 9.19 in North Macedonia. This means that students who reported frequent absenteeism only in Grade 4 showed mathematics achievement gains ranging from 2.70 to 9.19 points lower, respectively, than those of students in the same schools who reported rare absences in both grades, after controlling for all other variables in the model. That is, within the same school, students with similar Grade 4 mathematics achievement, home socioeconomic status, and similar reports of bullying exposure, sense of school belonging, instructional clarity in mathematics, and confidence in mathematics, are expected to have Grade 5 mathematics scores differing by about 7 to 9 points, if one reported being frequently absent only in Grade 4 and the other was rarely absent in both grades.

Similar to the Absenteeism Only model, the negative impact of frequent absenteeism only in Grade 5 seems to be more detrimental than absenteeism only in Grade 4, as evidenced by larger negative coefficients across eight of the nine participating education systems.^g The largest impact

^f The regression coefficient for frequent absence only in 2023 for Sweden is positive, although very small (0.23) and well within margin of error. Therefore, it should not be interpreted as meaningful.

^g The exception is Italy, where these coefficients are very similar.

of absenteeism only in Grade 5 was seen in North Macedonia, where, after controlling for all covariates in the model, students who reported frequent absenteeism are predicted to score, on average, 16.43 points lower than peers in the same schools who were rarely absent in both years.

Lastly, negative impacts of student-reported frequent absenteeism in both years were observed in all countries. These coefficients ranged from –3.44 in Sweden to –16.00 in North Macedonia. In some countries, these negative regression coefficients were several points larger than those for students who reported frequent absences only in Grade 5; however, in other countries, they were comparable across the two groups. The general trend suggests that frequent absenteeism is particularly detrimental to mathematics achievement when it occurs in the assessment year and is sometimes amplified when it persists across both years. These Full Model results, which account for other relevant predictors of achievement, are consistent with those obtained from the Absenteeism Only model.

Exhibit 12: Selected HLM Results, Impact of Frequent Absenteeism on Grade 5 (2024 Mathematics Achievement (Model 2, Full Model))

Country	Intercept		Grade 4 (2023 Mathematics Achievement		Home Socioeconomic Status		Frequent Absence, 2023 Only		Frequent Absence, 2024 Only		Frequent Absence in Both Years	
	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*
Georgia	519.73	7.17	0.74	0.03	3.22	0.78	-7.08	3.62	-8.50	3.03	-11.94	3.23
Italy	549.41	5.17	0.76	0.03	2.68	0.67	-2.82	3.80	-2.39	3.31	-5.61	4.35
Jordan	454.50	8.05	0.61	0.03	5.32	0.94	-7.30	4.06	-9.03	3.99	-13.35	3.82
Korea, Rep. of	624.86	5.34	0.84	0.04	1.27	0.98	-5.10	6.03	-9.32	6.85	-13.41	10.80
Kosovo	451.83	6.66	0.76	0.03	1.55	1.03	-2.70	3.57	-8.48	4.32	-8.45	3.83
Montenegro	492.82	3.20	0.67	0.03	5.36	0.96	-2.70	2.99	-12.14	3.03	-11.23	3.28
North Macedonia	489.52	4.98	0.63	0.03	4.86	1.06	-9.19	3.38	-16.43	3.74	-16.00	4.45
Slovenia	553.38	2.16	0.78	0.03	2.66	0.84	-3.51	2.89	-5.30	3.12	-5.29	4.05
Sweden	559.76	3.37	0.78	0.04	3.17	0.76	0.23	3.54	-4.48	2.86	-3.44	4.12

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system. See Estimates Pooling in [Appendix C](#) for further details.

The magnitude of regression coefficients for prior achievement is not directly comparable to those for the absenteeism variables because prior achievement is measured on a different scale.

See Exhibit C.8 for full model parameter estimates.

Overall, these results show evidence of a consistent negative impact of frequent absenteeism on Grade 5 mathematics achievement, even when controlling for other predictors. The association is typically strongest when absenteeism coincides with the assessment year and is either amplified or remains very strong when it persists across both years. Although in Kosovo, Montenegro, and North Macedonia the predictive power of frequent absenteeism during the assessment year is slightly stronger than persistent absenteeism across both years, the overarching picture is consistent: Frequent absenteeism, especially in the year of testing and when sustained across years, is consistently associated with lower Grade 5 mathematics achievement gains, even after controlling for empirically and conceptually relevant student-level covariates.

Science Achievement

Exhibit 13 shows selected results for science achievement. Overall, results are similar to those for mathematics and the Absenteeism Only science model, consistently pointing towards the negative impact of student-reported frequent absenteeism on science scores, with the largest impacts observed when frequent absenteeism occurs within the assessment year.

Student reports of frequent absenteeism in Grade 4 only are negatively associated with Grade 5 science achievement in all nine education systems, with regression coefficients ranging from -1.78 (Italy) to -7.13 (Georgia). Although the magnitude of these coefficients varies across countries, the consistent negative direction provides evidence that frequent absences in the year prior to the assessment are detrimental to students' science achievement, even after accounting for other relevant predictors.

When controlling for other covariates, student-reported frequent absenteeism only in Grade 5 is more detrimental than absenteeism in the year prior to the assessment, a result consistent across eight out of nine education systems. Specifically, the estimate of negative impact ranged from 7.07 points in Sweden to 15.93 points in North Macedonia. That is to say, compared to students who were rarely absent in both years, students who reported frequent absenteeism only in Grade 5 scored, on average, between approximately 7 and 16 points lower than students in the same school who were rarely absent in both years, holding constant all the covariates in the model. This consistent negative impact of absenteeism in the same year of the assessment on science achievement, above and beyond other relevant predictors, was also observed for the mathematics Full Model results. These results are also aligned with the negative impact on science score gains observed in the Absenteeism Only model. That is, absenteeism in the same year of the assessment is detrimental to science achievement growth, even after controlling for other relevant covariates.

Lastly, student reports of frequent absenteeism in both years are associated with lower Grade 5 science achievement in eight of the nine participating education systems, with coefficient estimates ranging from -6.85 (Jordan) to -14.98 (Kosovo).^h This means that students who reported frequent absenteeism in both years scored, on average, between 6.85 and 14.98 points lower than students in the same school who were rarely absent in both years, after controlling for all the covariates in the model. However, compounded negative impacts of absenteeism in both years on science achievement seem to be less severe than in mathematics, as the negative regression coefficients for frequent absenteeism in both years are less than those for frequent absenteeism only in Grade 5 in five countries. Among the other three countries with negative regression coefficients, the differences between these two are small.

Similar to what was observed for Grade 5 mathematics achievement and in the Absenteeism Only model for science, frequent absenteeism in either or both years is a consistent negative predictor of Grade 5 science achievement in most countries, even after accounting for other student-level covariates. As with other models, the negative associations are stronger when absenteeism occurs during the year of the assessment.

^h The exception is the estimate obtained for Italy, with this small positive regression coefficient is well within margin of error and therefore should not be interpreted as meaningful.

Exhibit 13: Selected HLM Results, Impact of Frequent Absenteeism on Grade 5 (2024) Science Achievement (Model 2, Full Model)

Country	Intercept		Grade 4 (2023) Science Achievement		Home Socioeconomic Status		Frequent Absence, 2023 Only		Frequent Absence, 2024 Only		Frequent Absence in Both Years	
	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*
Georgia	491.27	7.71	0.73	0.05	5.92	1.06	-7.13	4.03	-9.84	3.38	-11.02	2.95
Italy	541.35	4.49	0.75	0.04	3.09	0.67	-1.78	2.82	0.38	4.15	1.77	3.73
Jordan	450.90	7.71	0.69	0.04	4.04	1.02	-6.46	3.73	-7.57	4.17	-6.85	4.38
Korea, Rep. of	617.57	5.36	0.82	0.06	1.90	1.17	-4.65	7.64	-10.22	7.62	-8.35	10.96
Kosovo	411.04	5.36	0.68	0.05	1.71	0.96	-7.07	3.60	-13.94	3.77	-14.98	3.77
Montenegro	480.41	3.50	0.69	0.04	4.47	0.98	-2.88	3.09	-12.24	2.89	-12.64	3.26
North Macedonia	451.76	5.13	0.61	0.05	4.32	1.15	-5.37	2.92	-15.93	3.36	-14.43	3.87
Slovenia	561.36	2.18	0.73	0.04	2.77	1.15	-5.67	2.62	-10.22	3.26	-10.41	4.70
Sweden	560.24	3.85	0.75	0.06	3.75	0.91	-4.26	4.98	-7.07	3.12	-6.90	4.38

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system. See Estimates Pooling in [Appendix C](#) for further details.

The magnitude of regression coefficients for prior achievement is not directly comparable to those for the absenteeism variables because prior achievement is measured on a different scale.

See Exhibit C.9 for full model parameter estimates.

Key Takeaways

- 1. In Grades 4 and 5, regular school attendance is the norm for many students in the TIMSS 2023 Longitudinal education systems.** In seven of nine education systems, more than 50 percent of students were rarely absent in either assessment year. Conversely, 20 percent or less were frequently absent in both years for all nine education systems. Given the strong negative relationship between absences and academic achievement, further research is warranted to explore how best to support these students; however, it is encouraging to see that this group is relatively small in many systems. It is also worth noting that large increases in the number of students who report frequent absences between Grades 4 and 5 are not apparent.
- 2. Students who reported high rates of absenteeism in Grade 4 did not necessarily report the same level of absenteeism in Grade 5.** This is a positive finding, suggesting that frequent absences in one year, while still potentially harmful, do not necessarily imply that a student is on a long-term trajectory of showing frequent absences throughout schooling. Some students who report frequent absences in a single school year may be dealing with unusual circumstances (for example, illness, family issues) that are unlikely to recur the following year.
- 3. Students' reports of frequent absences in Grade 4, Grade 5, or both grades are strong negative predictors of mathematics and science achievement, with more recent absences appearing to be more detrimental.** In all education systems, students who reported frequent absences at some point tended to have lower Grade 5 achievement gains in both subjects compared to peers who never reported frequent absences, after accounting for prior achievement and other covariates. Generally speaking, impacts of frequent absences only in Grade 4 appear less harmful than frequent absenteeism only in Grade 5 or in both grades. This suggests that it may be possible for students to recoup missed learning due to absences over time, provided that frequent absences do not continue across multiple school years.

Future Directions

The results of this TIMSS Longitudinal Insights report shed new light on how student absences over two years of primary school are related to achievement in mathematics and science. Although the findings in this report are not necessarily surprising, they provide further support for the importance of ensuring students attend school. Additionally, the results provide evidence that more recent frequent absences are often more detrimental to student achievement than frequent absences in prior years of schooling. While there is some evidence of cumulative effects of absenteeism (especially in mathematics), this is a somewhat positive finding, in that students appear to be able to catch up on content missed during the previous school year, to some extent.

The results in this report also suggest areas for further research. Several of these relate to extensions of the HLM approach using more complex models. For example, the models presented in this report did not include any school-level variables and simply accounted for the variance explained by, and mean differences on student-level predictors of, these clusters. As expressed by ICCs presented in the Variance Decomposition section (as well as in [Appendix C](#) for complete-cases analysis), after accounting for the influence of student-level predictors in the models (Grade 4 achievement, home socioeconomic status, absenteeism, exposure to bullying, sense of belonging, confidence in each subject, and instructional clarity), school differences remain an important source of variation in mathematics and science achievement gains. Future work could incorporate school-level variables such as school socioeconomic composition or school resources to evaluate whether they moderate the relationship between student absences and academic achievement growth, as well as whether different school-level variables are more or less relevant across countries. Another possible HLM extension is more explicitly modeling change over time; whereas the model presented in this report incorporates Grade 4 achievement as a covariate in predicting Grade 5 achievement, other approaches could more directly model change in achievement across the two grades. Finally, this report uses a two-level model for each individual education system. Another possible approach would be to explicitly include the education system in the HLM in a third modeling level.

Further analyses could also examine characteristics of the students within each of the absenteeism classifications used in this report. For example, are there particular attributes that are associated with frequent absences in both years and are these consistent across countries? Exploration of these questions within countries could inform school leaders and policymakers in designing appropriate interventions to reduce student absences.

This report examined the relationship between achievement and reports of student absences in Grades 4 and 5. TIMSS 2023 Longitudinal also covered Grades 8 and 9; future work could replicate these analyses with data from the three countries that participated at these levels to see if the patterns observed here also hold for older students.

Other possible areas of future research include building upon the longitudinal nature of the study to examine potential interaction or moderation effects of other student-level characteristics (e.g., student socioeconomic status). For example, are students from households of lower socioeconomic status more likely to report frequent absences across both time points? Does home socioeconomic status moderate the relationship observed between student absences and academic achievement? Are these effects consistent across education systems and with the findings from prior research? Given prior research on home socioeconomic status and student absences, these questions are all worthy of exploration using TIMSS Longitudinal data.

The results in this report also indicate that the impacts of absenteeism may differ across mathematics and science, with potentially more severe negative effects in mathematics. One possibility is that mathematics content builds more cumulatively across Grades 4 and 5, whereas science is more likely to be taught as distinct topics within each year. Further national research efforts within education systems could examine the structure of mathematics and science curricula across grade levels.

Finally, it is important to note that the findings here are presented at a broad, international level and that recommendations for reducing student absences in individual countries are beyond the scope of this report. For example, within particular countries, there may be known school-level variables that affect student absences, or particular programs that have been shown to effectively mitigate any negative impacts of student absences. Further investigation within education systems could shed further light on the findings presented in this report and suggest productive avenues for policymaking or other interventions to bolster student attendance and, subsequently, student achievement.

Appendix A: About TIMSS 2023 Longitudinal

TIMSS 2023 Longitudinal is the first student-level longitudinal extension of TIMSS (Trends in International Mathematics and Science Study). TIMSS 2023 Longitudinal reassessed fourth- and eighth-grade students who participated in TIMSS 2023 one year later when most students were in the fifth and ninth grades. The study provides valuable insights into mathematics and science achievement growth and achievement differences across and within countries and helps policymakers and educators understand factors contributing to student learning.

The data presented in this report are based on a readministration of the mathematics and science achievement instruments as well as the Student Questionnaire administered at each time point. Students completed a questionnaire when they were first assessed in the fourth grade (2023) and again when they were reassessed in fifth grade (2024). Some questionnaire items were common across the two time points, and others were unique to a particular time point.

TIMSS 2023 Longitudinal also collected context questionnaire data in both assessment years from participating students' parents, teachers, and principals.

Many resources are available for obtaining more information about TIMSS 2023 and TIMSS 2023 Longitudinal, accessing the data, and conducting additional analyses. These resources include the publications listed below.

TIMSS 2023 Longitudinal Publications

- [*TIMSS 2023 Longitudinal International Results in Mathematics and Science*](#): provides a summary of student growth in mathematics and science between the fourth and fifth and eighth and ninth grades, as well as how contextual factors relate to students' achievement and growth.
- [*TIMSS 2023 Longitudinal Technical Report*](#): details operational and analytical procedures specific to TIMSS 2023 Longitudinal.
- [*TIMSS 2023 Longitudinal Context Questionnaires*](#): show the international versions of the contextual questionnaires to which students, parents, school principals, and teachers responded in 2024.
- [*TIMSS 2023 Longitudinal International Database*](#): includes data collected from the mathematics and science assessments and context questionnaires and achievement and contextual scale estimates, as well as estimates for growth in achievement between the two assessment years. The accompanying User Guide provides information about database contents and analysis resources.

TIMSS 2023 Publications Relevant to TIMSS 2023 Longitudinal

- [*TIMSS 2023 Assessment Frameworks*](#): provides information about the TIMSS 2023 mathematics and science assessments, context questionnaires, and assessment design.
- [*TIMSS 2023 Encyclopedia*](#): contains information about national contexts for countries participating in TIMSS 2023, including a chapter written by each country describing its educational system and responses to the TIMSS 2023 Curriculum Questionnaires.

- [*TIMSS 2023 Technical Report: Methods and Procedures*](#): details instrument development, sample design and implementation, operations, and analytical procedures. Many of these procedures were also employed in TIMSS 2023 Longitudinal.
- [*TIMSS 2023 Context Questionnaires*](#): show the international versions of the contextual items to which students, parents, school principals, teachers, and National Research Coordinators responded in 2023.

Appendix B: Context Questionnaire Items and Scales Included in Analysis

All contextual variables included in the analysis come from the Student Questionnaires administered in addition to the achievement tests in 2023 and 2024. Students' reports of absences constitute the focal variables of this study; other variables were selected based on other exploratory analyses and relationships with achievement observed in the [TIMSS 2023 International Results](#) and [TIMSS 2023 Longitudinal International Results](#).

Additional information about the context scales (e.g., scale items, reliability) included in the analysis is available in [Chapter 15](#) of the *TIMSS 2023 Technical Report*. Items in all scales were identical across the two time points.

Exhibit B.1 shows the scale or item variable names for the analysis variables from each year of data collection (2023 or 2024). Note that only the 2023 variable was used for Home Socioeconomic Status — Parents' Reports. Students' home socioeconomic status was not expected to change between the two assessment years, and the 2023 variable had more complete data.

Exhibit B.1: Analysis Items and Scales

Scale or Item Description	Scale or Item Variable Name (2023)	Scale or Item Variable Name (2024)
Frequency of Student Absences (item)	ASBG08	ASBLG06
Home Socioeconomic Status – Parents' Reports (scale)	ASBHSES	–
Students' Sense of School Belonging (scale index)	ASDGSSB	ASDLGSSB
Student Bullying (scale index)	ASDGSB	ASDLGSB
Students Confident in Mathematics (scale index)	ASDGSCM	ASDLGSCM
Students Confident in Science (scale index)	ASDGSCS	ASDLGSCS
Instructional Clarity in Mathematics Lessons (scale index)	ASDGICM	ASDLGICM
Instructional Clarity in Science Lessons (scale index)	ASDGICS	ASDLGICS

Appendix C: Technical Details of HLM Analysis

Data Preparation

Before analyses, country-level datasets for student achievement, student context, and home context were created and merged into a single multicountry dataset using country, school, classroom, and student identifiers. Predictors of interest in both years (2023 and 2024), including absenteeism, bullying, sense of belonging, student confidence, and instructional clarity, were recoded into single dummy-coded variables for each year. For each set of dummy variables, the most positive category (e.g., rare absences in both years, rare bullying in both years) was used as the reference category. A summary of the year-specific recoding scheme is shown in Exhibit C.1 below.

Exhibit C.1: Predictors Recoding Scheme by Assessment Year

Label	Variables (2023/2024)	Original Scheme	Recoding
Absenteeism Frequency	ASBG08 ASBLG06	1: Once a week	1: Frequent Absenteeism
		2: Once every two weeks	
		3: Once a month	0: Rare Absenteeism
		4: Rare	
		5: Never or almost never	
Bullying Frequency	ASDGSB ASDLGSB	1: Never or Almost Never	0: Rare Bullying
		2: About Monthly	1: Frequent Bullying
		3: About Weekly	
Sense of School Belonging	ASDGSSB ASDLGSSB	1: High Sense of School Belonging	0: High/Some Sense of School Belonging
		2: Some Sense of School Belonging	1: Little Sense of School Belonging
		3: Little Sense of School Belonging	
Mathematics Confidence	ASDGSCM ASDLGSCM	1: Very Confident in Mathematics	0: Very/Somewhat Confident in Mathematics
		2: Somewhat Confident in Mathematics	1: Not Confident in Mathematics
		3: Not Confident in Mathematics	
Science Confidence	ASDGSCS ASDLGSCS	1: Very Confident in Science	0: Very/Somewhat Confident in Science
		2: Somewhat Confident in Science	1: Not Confident in Science
		3: Not Confident in Science	
Instructional Clarity Mathematics	ASDGICM ASDLGICM	1: High Clarity of Instruction	0: High/Moderate Clarity of Mathematics Instruction
		2: Moderate Clarity of Instruction	1: Low Clarity of Mathematics Instruction
		3: Low Clarity of Instruction	
Instructional Clarity Science	ASDGICS ASDLGICS	1: High Clarity of Instruction	0: High/Moderate Clarity of Science Instruction
		2: Moderate Clarity of Instruction	1: Low Clarity of Science Instruction
		3: Low Clarity of Instruction	

The dummy variables were used to create multicategorical variables to indicate no predictor prevalence in either year (0), prevalence in 2023 only (1), prevalence in 2024 only (2), and prevalence in both years (3). If the original variables had missing data in any year, the new variables were recoded as missing as well. Distributions and proportions of missing data for multicategorical variables are shown in Exhibit C.2. All variables were converted to labeled factors. Recoding accuracy was verified through descriptive comparisons between original variables and derived indicators, including country-level weighted summaries of all newly created measures.

Exhibit C.2: Multicategorical Variable Distributions and Missing Data Proportions

	Georgia		Italy		Jordan		Korea, Rep. of		Kosovo		Montenegro		North Macedonia		Slovenia		Sweden		Overall	
Variable	N = 4,491		N = 4,610		N = 6,172		N = 4,507		N = 4,747		N = 4,559		N = 4,866		N = 5,015		N = 5,358		N = 44,325	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Absenteeism																				
Rare Absence in Both Years	1,762	48.0	3,036	77.2	2,256	45.8	3,374	95.5	2,567	63.6	2,533	63.4	2,239	55.5	3,143	79.0	3,401	78.4	24,311	66.7
Frequent Absence in 2023 / Rare Absence in 2024	516	14.1	390	9.9	885	18.0	87	2.5	627	15.5	643	16.1	722	17.9	396	10.0	316	7.3	4,582	12.6
Rare Absence in 2023 / Frequent Absence in 2024	638	17.4	270	6.9	918	18.7	45	1.3	450	11.2	471	11.8	550	13.6	276	6.9	411	9.5	4,029	11.1
Frequent Absence in Both Years	753	20.5	236	6.0	864	17.6	28	0.8	393	9.7	351	8.8	523	13.0	164	4.1	209	4.8	3,521	9.7
Percent Missing	18.3		14.71		20.24		21.59		14.96		12.31		17.1		20.66		19.06		17.78	
Bullying																				
Rare Bullying in Both Years	2,795	82.1	3,191	82.2	2,749	58.8	3,310	93.6	2,835	74.1	2,709	74.3	2,331	66.1	3,312	83.5	3,827	90.8	27,059	78.0
Frequent Bullying in 2023 / Rare Bullying in 2024	264	7.8	358	9.2	687	14.7	98	2.8	359	9.4	368	10.1	435	12.3	344	8.7	143	3.4	3,056	8.8
Rare Bullying in 2023 / Frequent Bullying in 2024	216	6.4	179	4.6	757	16.2	94	2.7	384	10.0	338	9.3	433	12.3	197	5.0	174	4.1	2,772	8.0
Frequent Bullying in Both Years	129	3.8	154	4.0	483	10.3	34	1.0	246	6.4	230	6.3	330	9.4	116	2.9	73	1.7	1,795	5.2
Percent Missing	24.2		15.79		24.24		21.54		19.44		20.05		27.48		20.86		21.3		21.76	
Sense of School Belonging																				
High or Some Sense of School Belonging in Both Years	2,985	87.4	3,059	79.7	3,678	78.3	2,973	84.4	3,490	93.8	3,076	83.9	3,237	90.6	2,811	71.8	3,141	74.6	28,450	82.3
Little Sense of School Belonging in 2023 / High or Some Sense of School Belonging in 2024	71	2.1	245	6.4	337	7.2	208	5.9	69	1.9	163	4.5	120	3.4	294	7.5	216	5.1	1,723	5.0
High or Some Sense of School Belonging in 2023 / Little Sense of School Belonging in 2024	308	9.0	314	8.2	512	10.9	220	6.2	139	3.7	341	9.3	181	5.1	511	13.1	564	13.4	3,090	8.9
Little Sense of School Belonging Both Years	53	1.6	221	5.8	172	3.7	122	3.5	22	0.6	87	2.4	36	1.0	298	7.6	288	6.8	1,299	3.8
Percent Missing	23.91		16.72		23.87		21.83		21.63		19.57		26.55		21.95		21.44		22.03	
Confidence in Mathematics																				
No Not Confident in Mathematics	2,099	62.6	2,307	61.8	2,143	48.2	1,858	54.3	2,063	57.8	1,857	53.8	1,737	52.5	2,190	57.7	2,582	63.3	18,836	56.8
Not Confident in Mathematics in 2023 / Very or Somewhat Confident in Mathematics in 2024	333	9.9	386	10.4	853	19.2	375	11.0	394	11.0	402	11.6	490	14.8	413	10.9	327	8.0	3,973	12.0
Very or Somewhat Confident in Mathematics in 2023 / Not Confident in Mathematics in 2024	544	16.2	497	13.3	848	19.1	413	12.1	649	18.2	686	19.9	582	17.6	547	14.4	534	13.1	5,300	16.0
Not Confident in Mathematics in Both Years	376	11.2	541	14.5	601	13.5	778	22.7	463	13.0	510	14.8	502	15.2	648	17.1	639	15.7	5,058	15.3
Percent Missing	25.36		19.07		27.98		24.03		24.82		24.22		31.96		24.27		23.81		25.17	

Multicategorical variables distributions relative to valid data.

Percent missing relative to total sample size.

Exhibit C.2: Multicategorical Variable Distributions and Missing Data Proportions (Continued)

	Georgia		Italy		Jordan		Korea, Rep. of		Kosovo		Montenegro		North Macedonia		Slovenia		Sweden		Overall	
Variable	N = 4,491		N = 4,610		N = 6,172		N = 4,507		N = 4,747		N = 4,559		N = 4,866		N = 5,015		N = 5,358		N = 44,325	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Confidence in Science																				
No Not Confident in Science	1,685	53.0	2,400	64.6	1,735	39.8	1,802	51.9	1,643	45.8	1,594	47.2	1,183	36.9	2,055	53.9	2,556	63.7	16,653	50.9
Not Confident in Science in 2023 / Very or Somewhat Confident in Science in 2024	499	15.7	484	13.0	816	18.7	416	12.0	521	14.5	482	14.3	487	15.2	552	14.5	439	10.9	4,696	14.4
Very or Somewhat Confident in Science in 2023 / Not Confident in Science in 2024	507	16.0	440	11.9	963	22.1	662	19.1	737	20.5	663	19.7	739	23.1	594	15.6	558	13.9	5,863	17.9
Not Confident in Science in Both Years	486	15.3	390	10.5	850	19.5	593	17.1	690	19.2	635	18.8	794	24.8	611	16.0	463	11.5	5,512	16.8
Percent Missing	29.26		19.44		29.29		22.94		24.35		25.99		34.18		23.99		25.05		26.17	
Instructional Clarity in Mathematics																				
No Low Instructional Clarity in Mathematics	3,259	95.6	3,394	89.4	3,823	87.0	3,254	92.2	3,606	95.8	3,331	91.9	3,301	95.1	3,504	89.4	3,660	87.4	31,132	91.3
Low Instructional Clarity in Mathematics in 2023 / High or Moderate Clarity of Instruction in Mathematics in 2024	45	1.3	106	2.8	255	5.8	105	3.0	62	1.7	105	2.9	75	2.2	128	3.3	139	3.3	1,020	3.0
High or Moderate Clarity of Instruction in Mathematics in 2023 / Low Instructional Clarity in Mathematics in 2024	102	3.0	241	6.4	256	5.8	152	4.3	85	2.3	173	4.8	83	2.4	242	6.2	312	7.5	1,646	4.8
Low Instructional Clarity in Mathematics in Both Years	4	0.1	55	1.5	61	1.4	17	0.5	10	0.3	14	0.4	11	0.3	44	1.1	77	1.8	293	0.9
Percent Missing	24.07		17.66		28.79		21.72		20.73		20.53		28.69		21.87		21.84		23.09	
Instructional Clarity in Science																				
No Low Instructional Clarity in Science	3,160	95.2	3,368	89.0	3,777	86.4	3,134	89.0	3,536	96.2	3,201	91.3	3,147	93.3	3,460	89.8	3,514	85.1	30,297	90.4
Low Instructional Clarity in Science in 2023 / High or Moderate Clarity of Instruction in Science in 2024	54	1.6	129	3.4	255	5.8	141	4.0	62	1.7	117	3.3	71	2.1	115	3.0	156	3.8	1,100	3.3
High or Moderate Clarity of Instruction in Science in 2023 / Low Instructional Clarity in Science in 2024	96	2.9	229	6.1	284	6.5	217	6.2	73	2.0	171	4.9	142	4.2	233	6.1	365	8.8	1,810	5.4
Low Instructional Clarity in Science in Both Years	8	0.2	58	1.5	54	1.2	29	0.8	4	0.1	16	0.5	14	0.4	46	1.2	96	2.3	325	1.0
Percent Missing	26.12		17.92		29.2		21.88		22.58		23.12		30.66		23.15		22.9		24.35	

Multicategorical variables distributions relative to valid data.
Percent missing relative to total sample size.

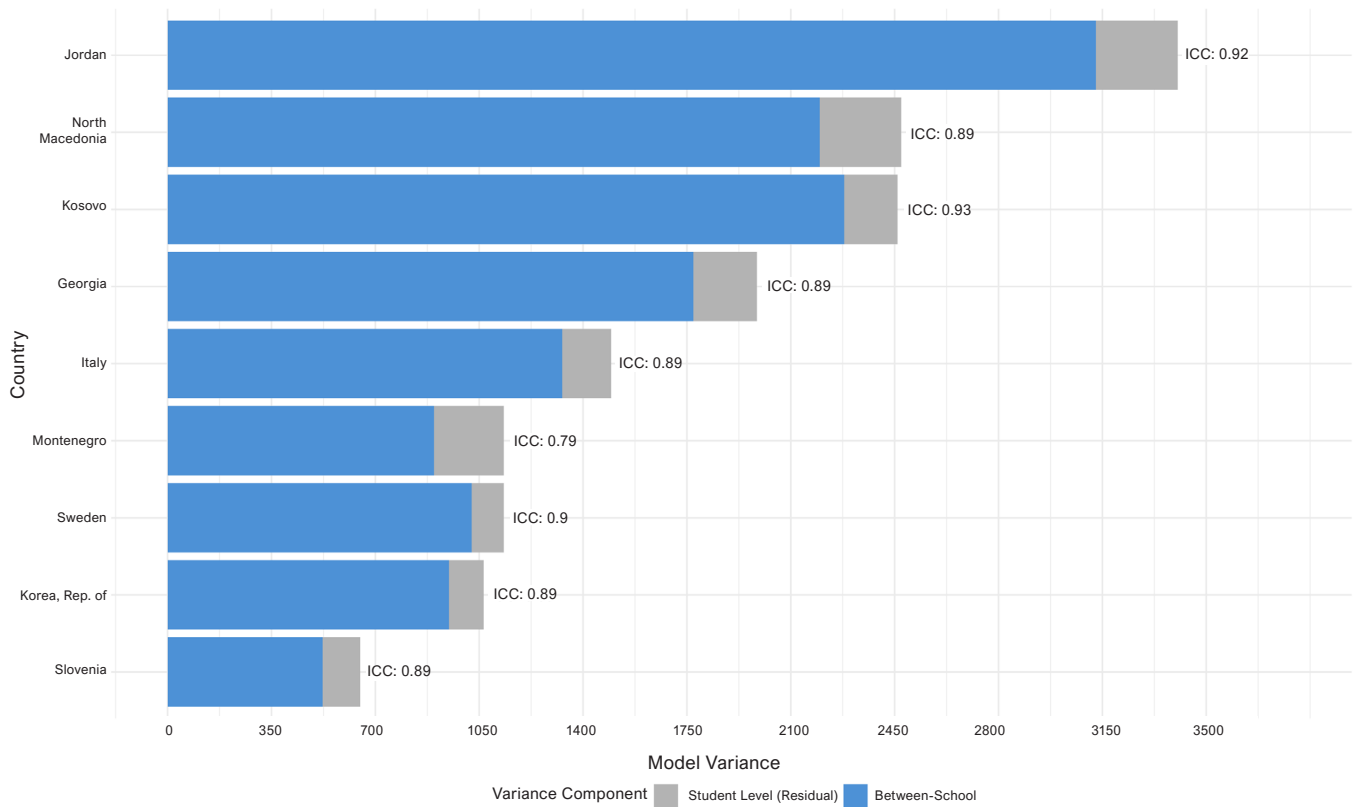
Complete-Case Conditional Intraclass Correlations

Exhibits C.3 presents the variance partitioning results from the complete-case HLMs (Full Model) across all participating education systems, distinguishing between student-level (gray) and school-level (blue/green) variance components. For each education system, the graphs also display the intra-class correlations (ICCs), which quantify the proportion of total variance attributable to between-school differences after accounting for all predictors included in the final models. For both mathematics and science achievement models, these ICC values are relatively high across all systems, ranging from 0.79 in Montenegro to 0.93 in Kosovo for mathematics, from 0.79 in Slovenia to 0.93 in Jordan for science.

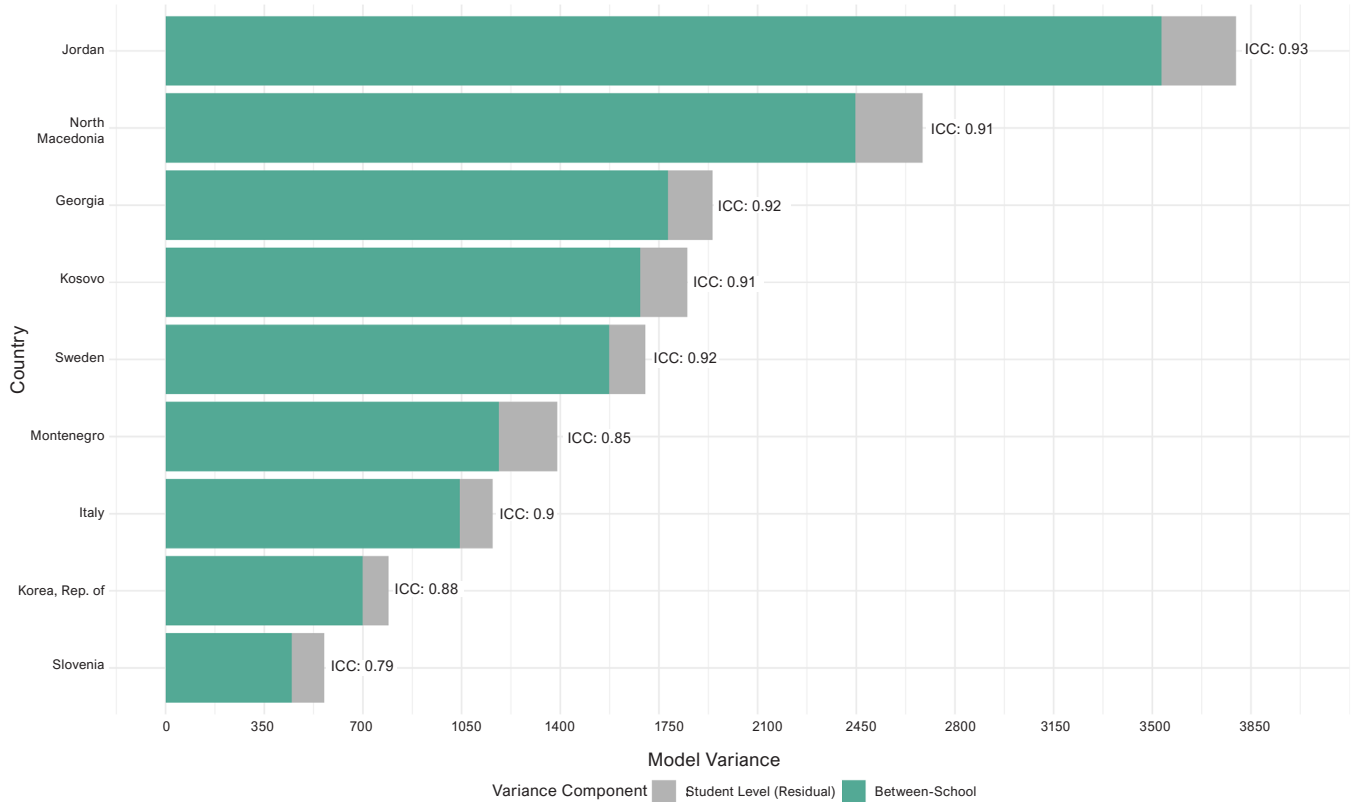
The relatively high ICC estimates are consistent with the modeling strategy. The inclusion of school-centered level-1 predictors systematically reduces within-school (student-level) residual variance while leaving between-school variance largely unchanged. Since group-mean centering removes all between-school variation from level-1 covariates, school-level variance remains unaffected. The reported ICCs should therefore be interpreted as conditional ICCs, reflecting the predominance of unexplained between-school variance after accounting for student-level heterogeneity, rather than as simple unconditional measures of clustering.

Exhibit C.3: Complete-case Variance Decomposition and Conditional ICC by Country**Mathematics**

ICC: proportion of between-school variance after accounting for student-level predictors

**Science**

ICC: proportion of between-school variance after accounting for student-level predictors



Imputation Phase

Imputation Strategy

Multiple imputation for missing contextual indicators was conducted using Multiple Imputation by Chained Equations (MICE)^{80,81} under a Fully Conditional Specification (FCS) framework,^{82,83} implemented separately within each country to avoid cross-country pooling. Imputation models were aligned with the planned multilevel analysis structure, with students nested within schools, and used two-level predictive mean matching to impute student-level (level-1) predictors within schools.^{84,85,86,87} The FCS imputation predictor matrix was specified to prevent self-prediction, excluding complete variables and the cluster ID variables from imputation and allowing mutual prediction among incomplete level-1 variables. The procedure used school-level averages and plausible values for mathematics achievement in 2023 and 2024 as predictors in the imputation model. The latter helped in preserving within- and between-school variance components while maintaining realistic values through predictive mean matching. Imputation was executed in R using the mice package.⁸⁸ The procedure involved 50 FCS iterations, a 10-iteration warm-start, and fixed random seeds to ensure reproducibility, yielding 10 imputed datasets for each country. Imputation was performed with all five sets of 2023 and 2024 mathematics achievement plausible values, resulting in 50 total imputed datasets for each country.

Imputation Diagnostics

Chain (trace), density, and strip plots were examined by country to evaluate the efficacy and quality of the imputation procedure. For each variable, chain plots display summaries for means and standard deviations of the imputed values across iterations for each imputation chain, providing information for assessing convergence and mixing of the FCS algorithm. Well-behaved chains should look stationary, with no clear or systematic drift or trend, and different chains should overlap to indicate the coverage of similar regions. Ideally, early iterations (burn-in) should show some unstable transients, with later segments showing similar variance distributions. Overall, the chain plots showed that the imputation algorithm provides stable imputations across countries. Exhibit C.4 shows examples of chain-mixing plots for the absenteeism, bullying, and sense-of-belonging predictors. For each country panel, the left column shows the iteration-by-iteration completed-data mean. The right column shows the corresponding within-imputation standard deviation (sd); the xaxis shows the Gibbs iteration (0–50). Each colored line represents a parallel imputation chain (one per imputed dataset). Across variables and countries, the traces form compact bands with substantial overlapping among chains and no visible deviations, trends, or chain separation. The behavior of both the mean and the standard deviation is consistent (i.e., centered and bounded), which indicates good cross-chain mixing, stationarity, and no evidence of multimodality or degeneracy across the imputations.

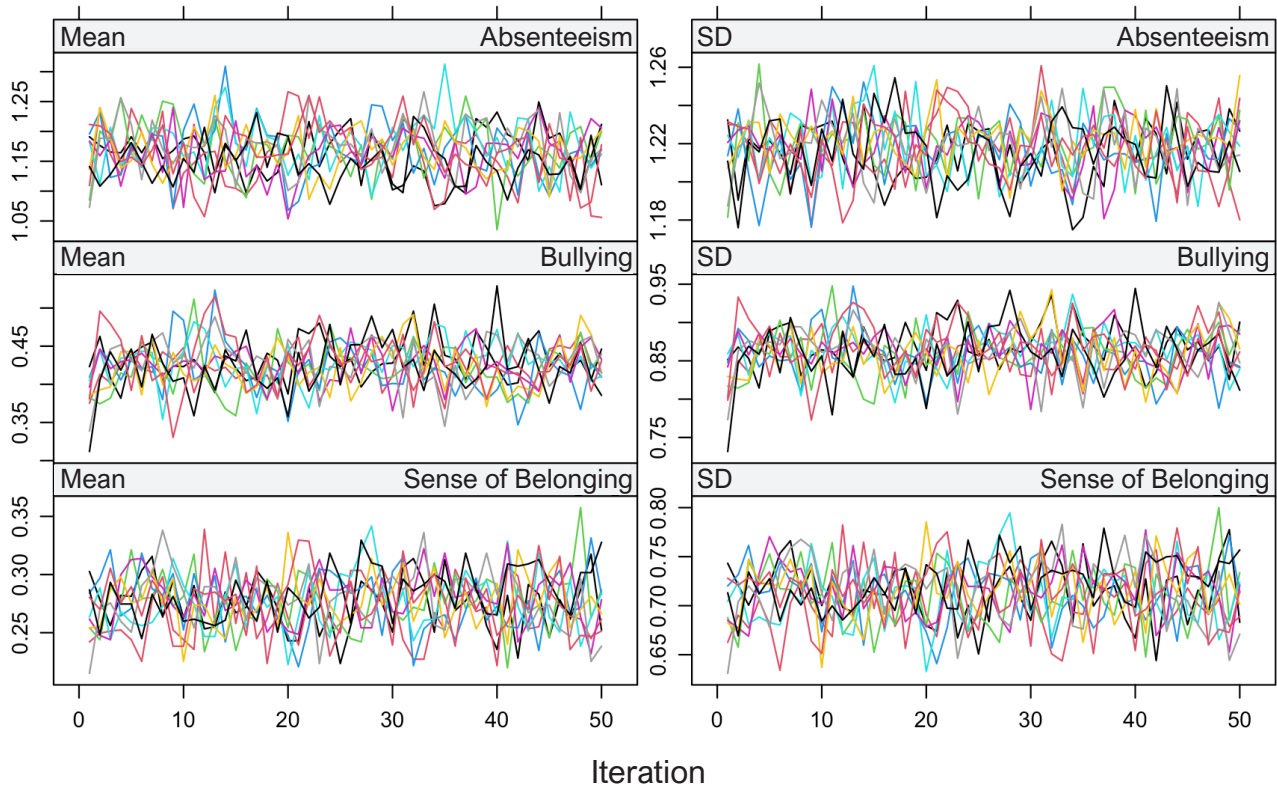
Strip plots displaying individual observed and imputed values were used to inspect the overlap between imputed and observed values to identify potential out-of-range observations. Overall, the strip plots indicated that the imputation procedure yielded coherent, plausible values for all predictors. Imputed points appear interleaved with observed points in plausible regions, without clustering in narrow bands or creating artificial gaps. Implausible situations, such as imputed values piling up at boundaries or values outside the variable range, would indicate the need to refine predictor sets, add constraints, or respecify the imputation model. Exhibit C.5 displays example plots for the absenteeism variable for all participating countries. The horizontal

axis shows the imputation number, and the vertical axis shows the observed or imputed response categories (0–3). The plots show that imputed values are strictly confined to the valid response categories and closely mirror the observed data, as expected under predictive mean matching. This consistency indicates that the imputation model preserves the discrete, ordinal nature of the items and does not introduce implausible values.

Lastly, density plots were used to diagnose whether imputations are plausible and consistent with the observed data, using kernel density overlays to compare observed values to those produced by the imputation models. Overall, the density of imputed values was reasonably aligned with the observed distribution. No discrepancies were identified between observed and imputed curves that warranted revisiting the imputation model specification (predictors, transformations, interactions, etc.). Exhibit C.6 shows observed response distributions (blue lines) and imputed response distributions dataset (magenta lines) for the absenteeism, bullying, and sense of belonging predictors. The horizontal axis maps the original ordinal response scale (0–3 categories), and the vertical axis is density. Across countries, the imputed densities closely tracked the observed densities, reproducing the large proportion of cases in the lowest category and relatively smaller proportions at higher categories. The tight alignment and limited divergence across the imputation densities indicate that the imputation model generated plausible values that closely resemble the ordinal, multimodal nature of the items. A comparison between models estimated on complete-case and pooled imputed data is provided in Exhibits C.10 and C.11.

Exhibit C.4: Chain-Mixing Plots for Absenteeism, Bullying, and Belonging Predictors

Georgia



Italy

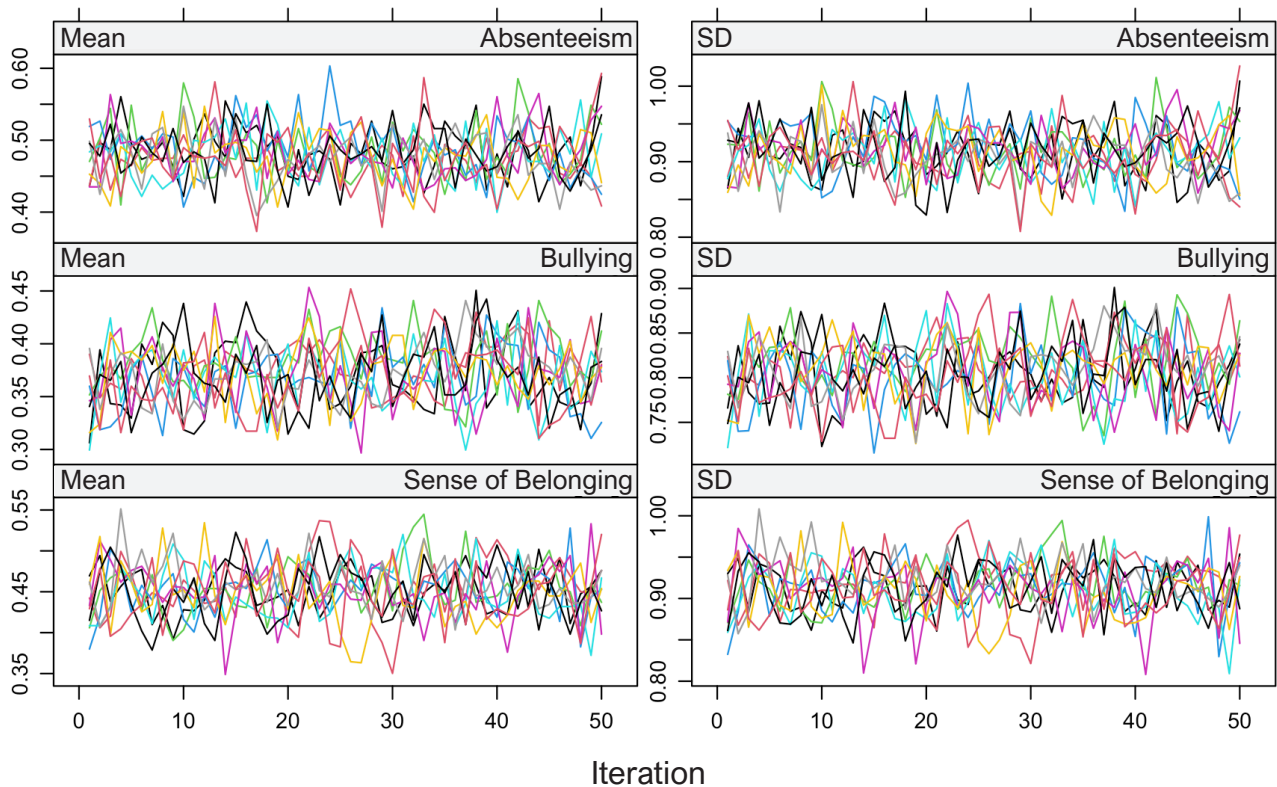
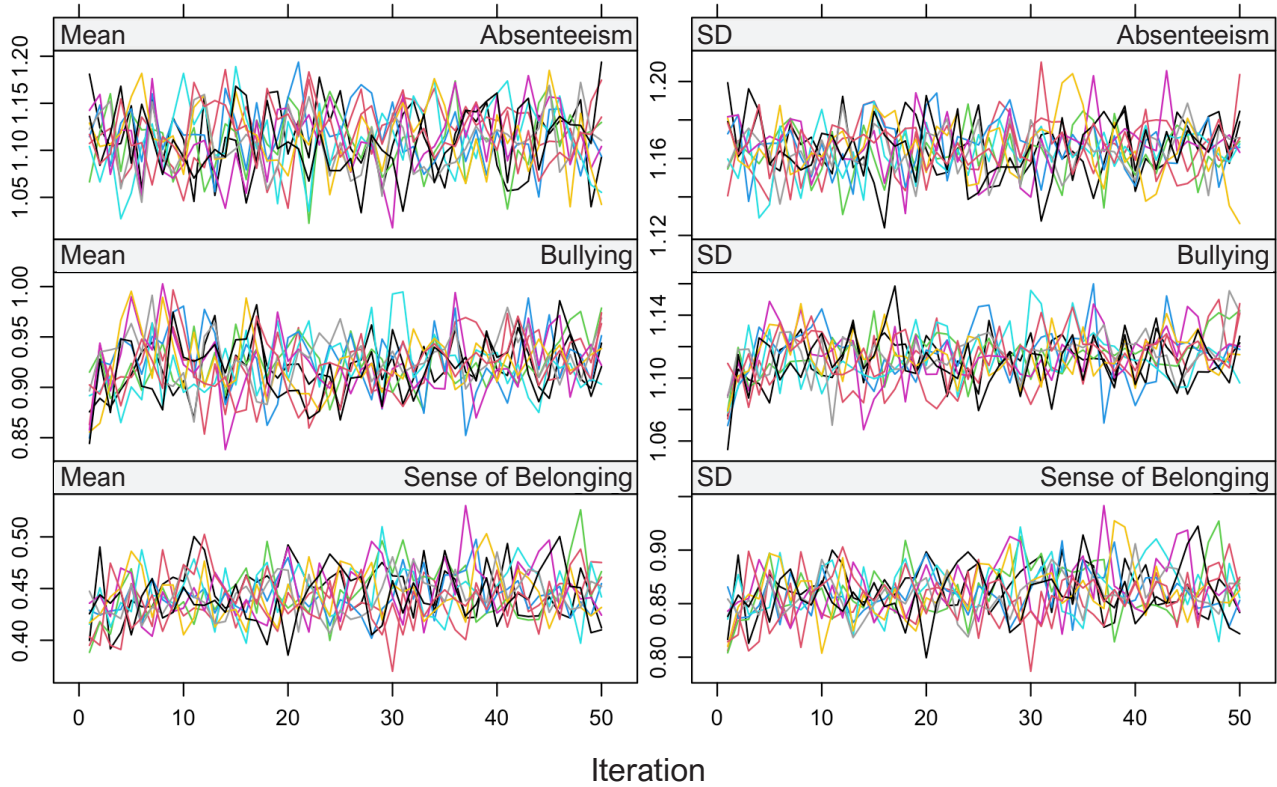


Exhibit C.4: Chain-Mixing Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)

Jordan



Korea, Rep. of

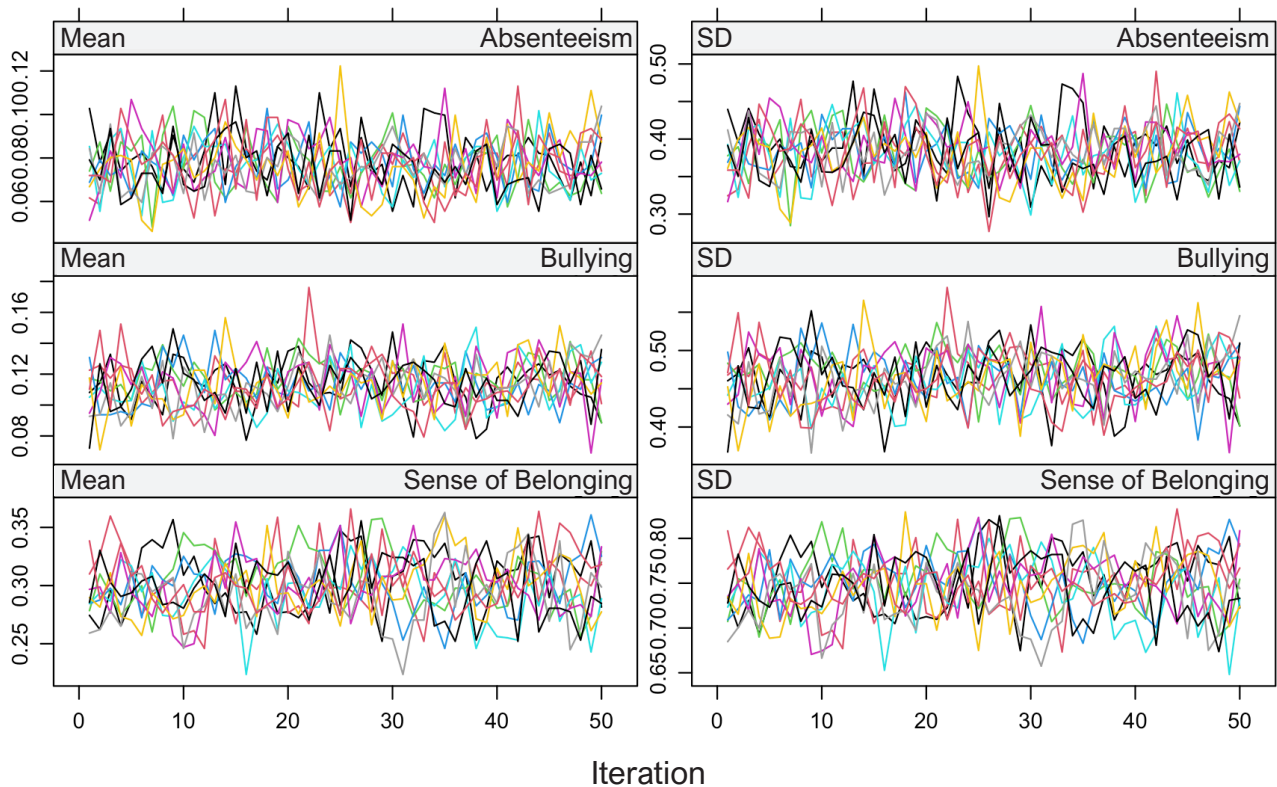
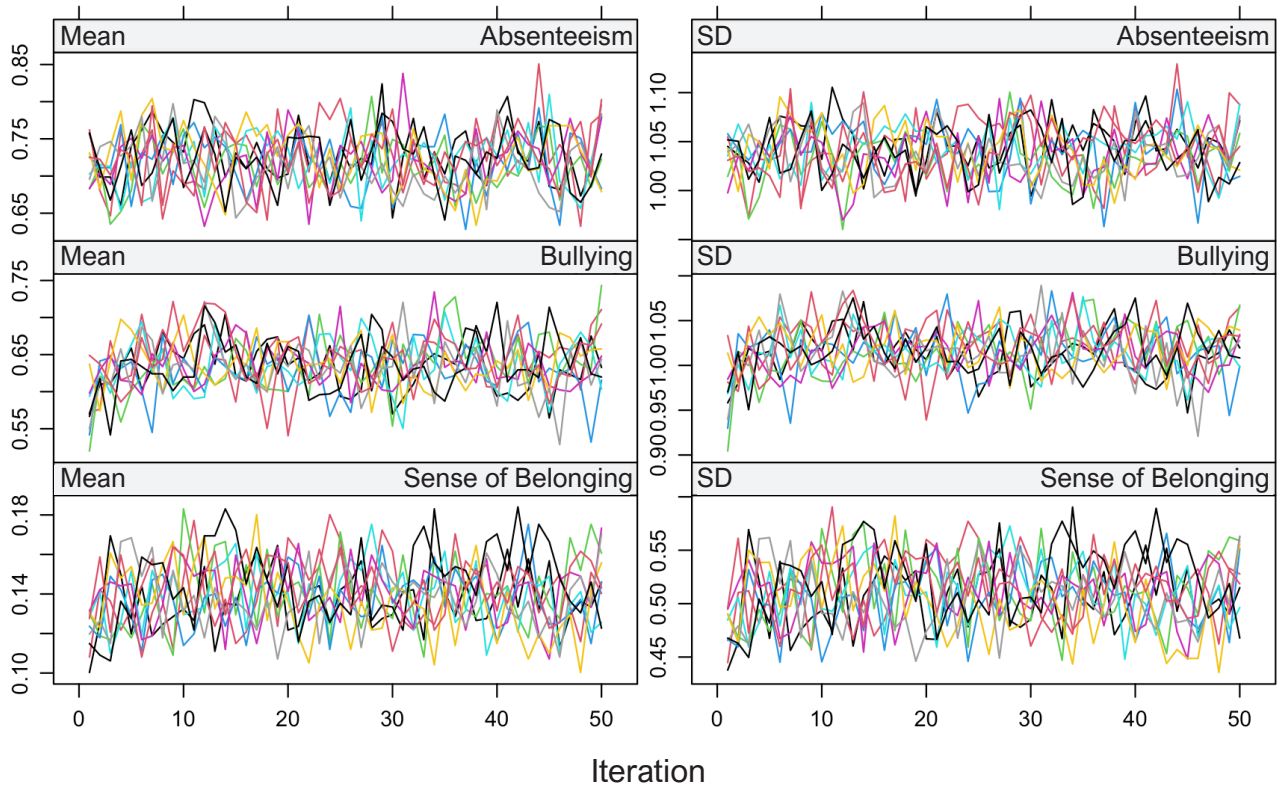


Exhibit C.4: Chain-Mixing Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)

Kosovo



Montenegro

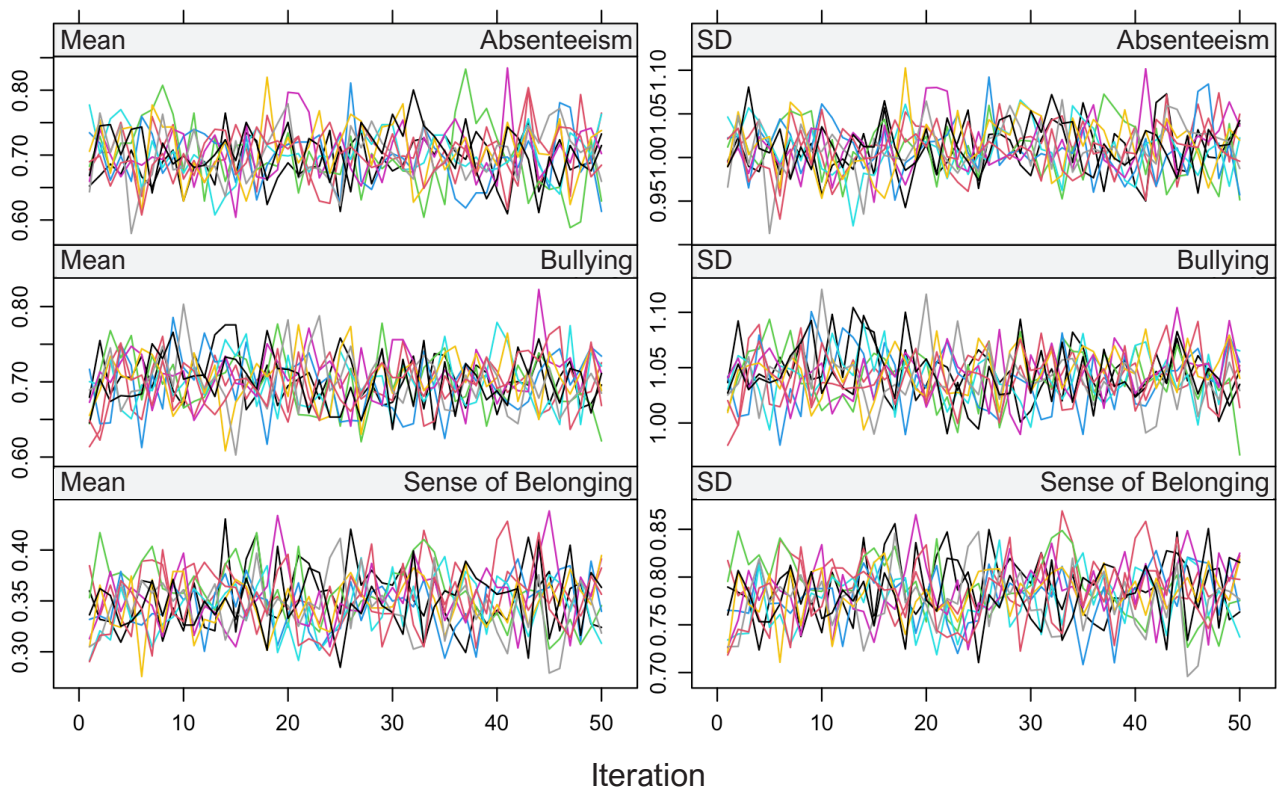
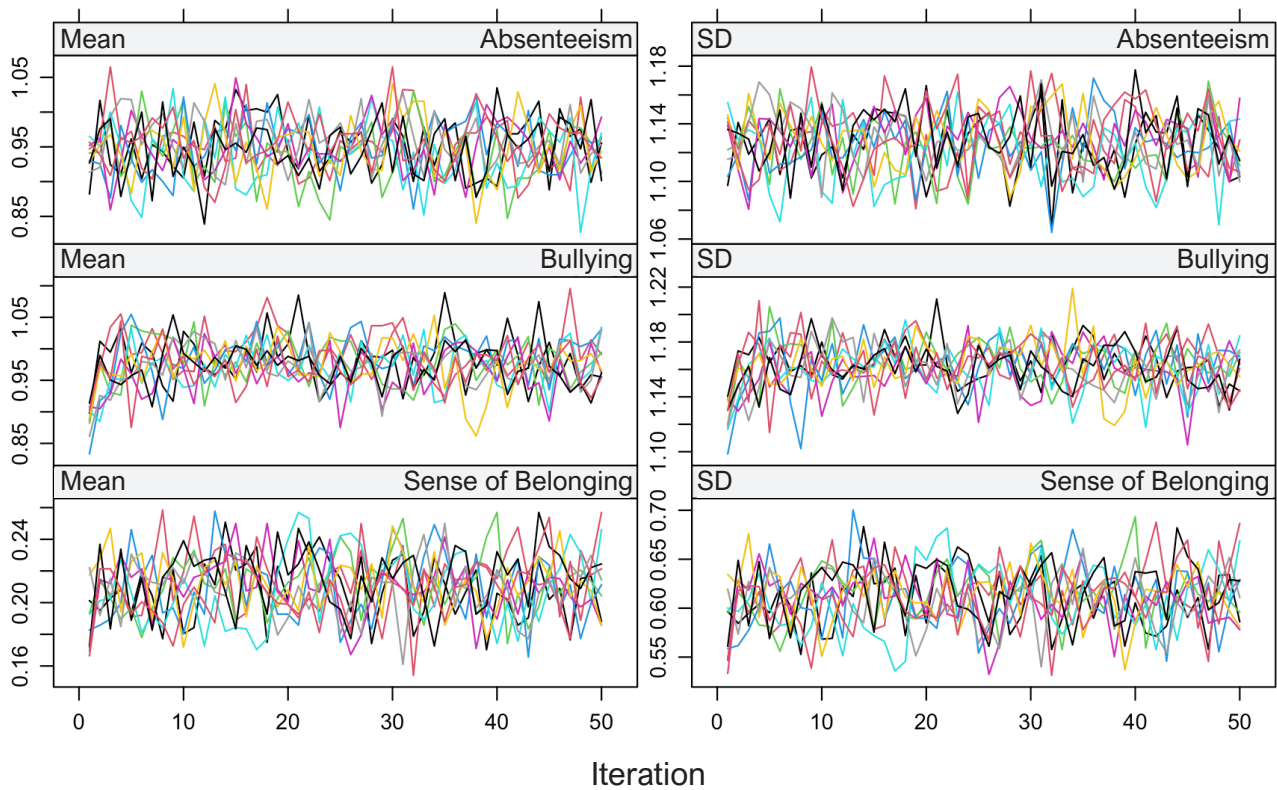


Exhibit C.4: Chain-Mixing Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)

North Macedonia



Slovenia

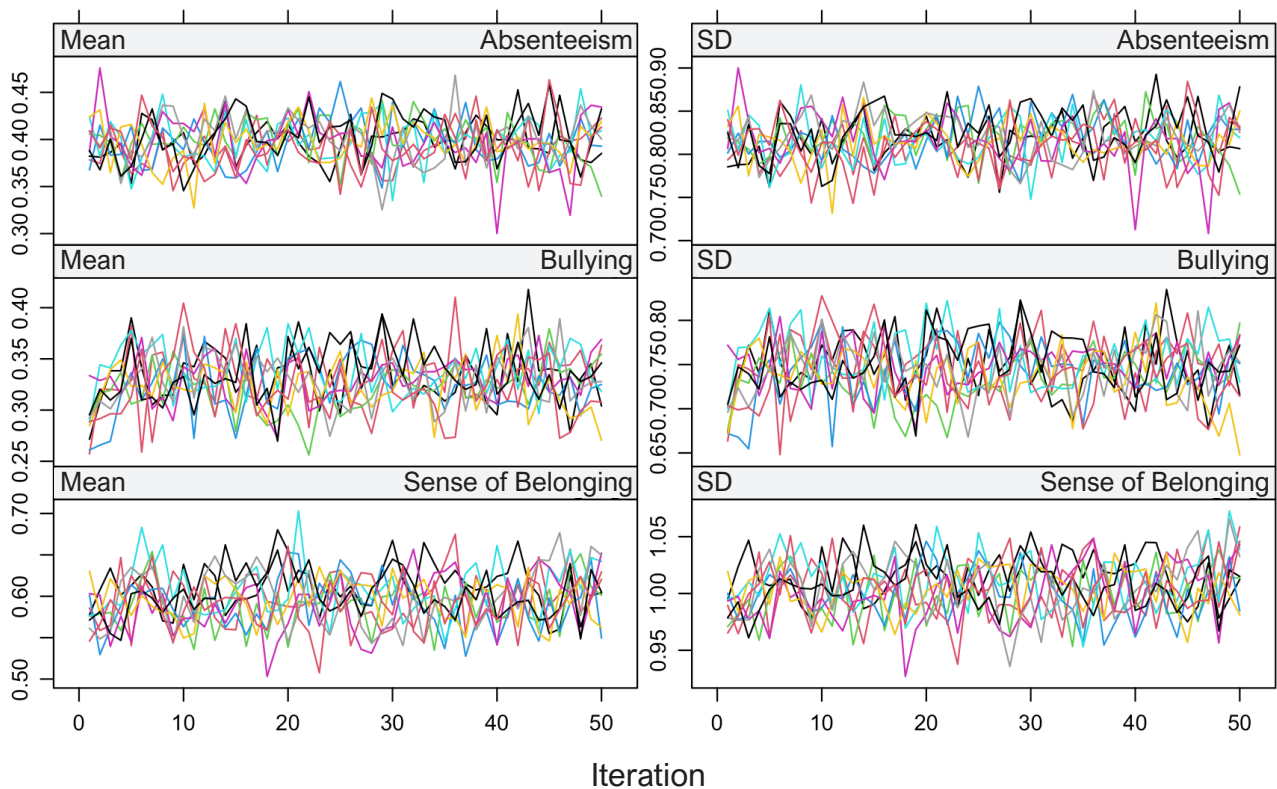


Exhibit C.4: Chain-Mixing Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)

Sweden

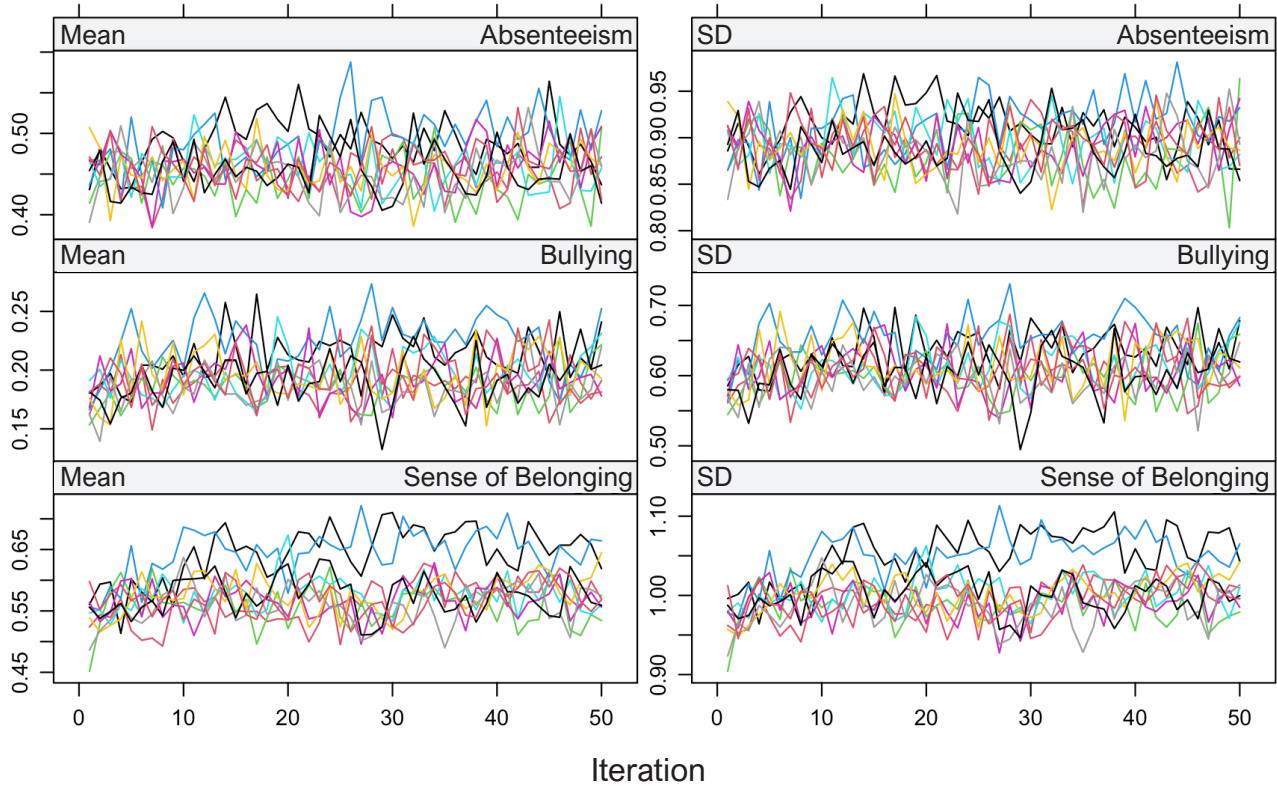


Exhibit C.5: Strip Plots for Absenteeism Predictor

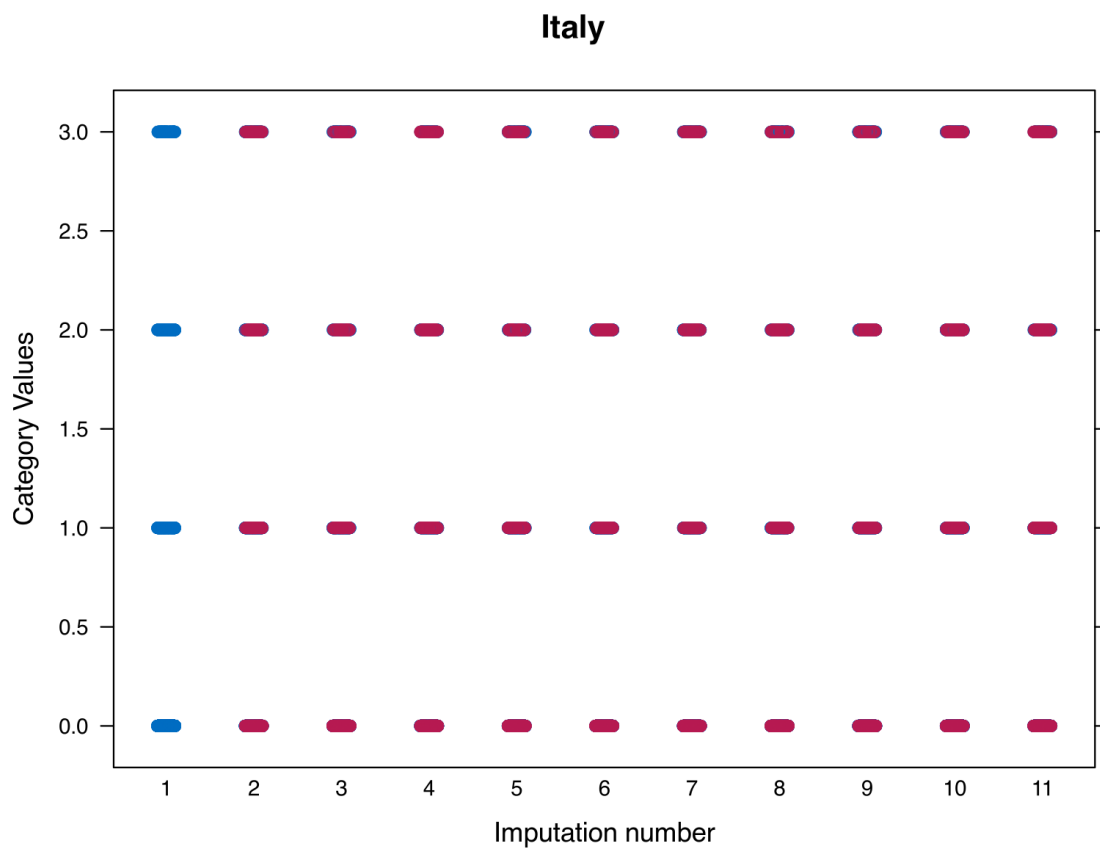
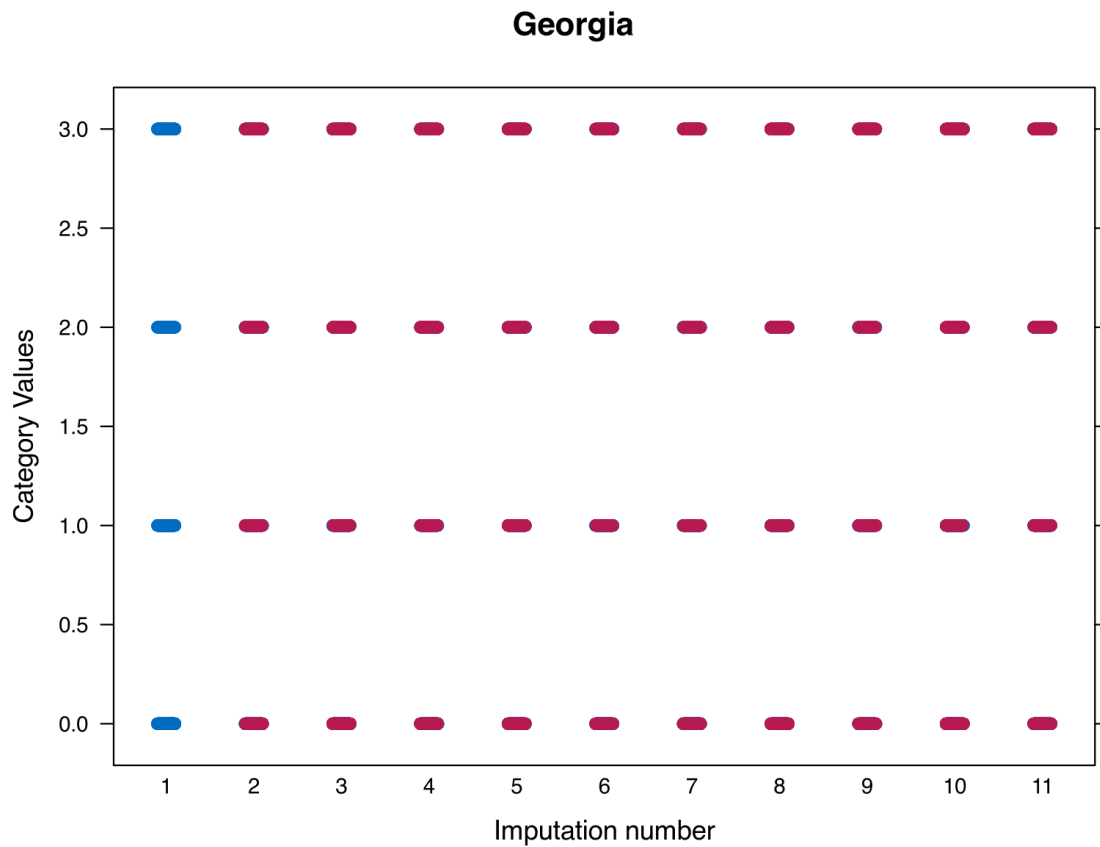


Exhibit C.5: Strip Plots for Absenteeism Predictor (Continued)

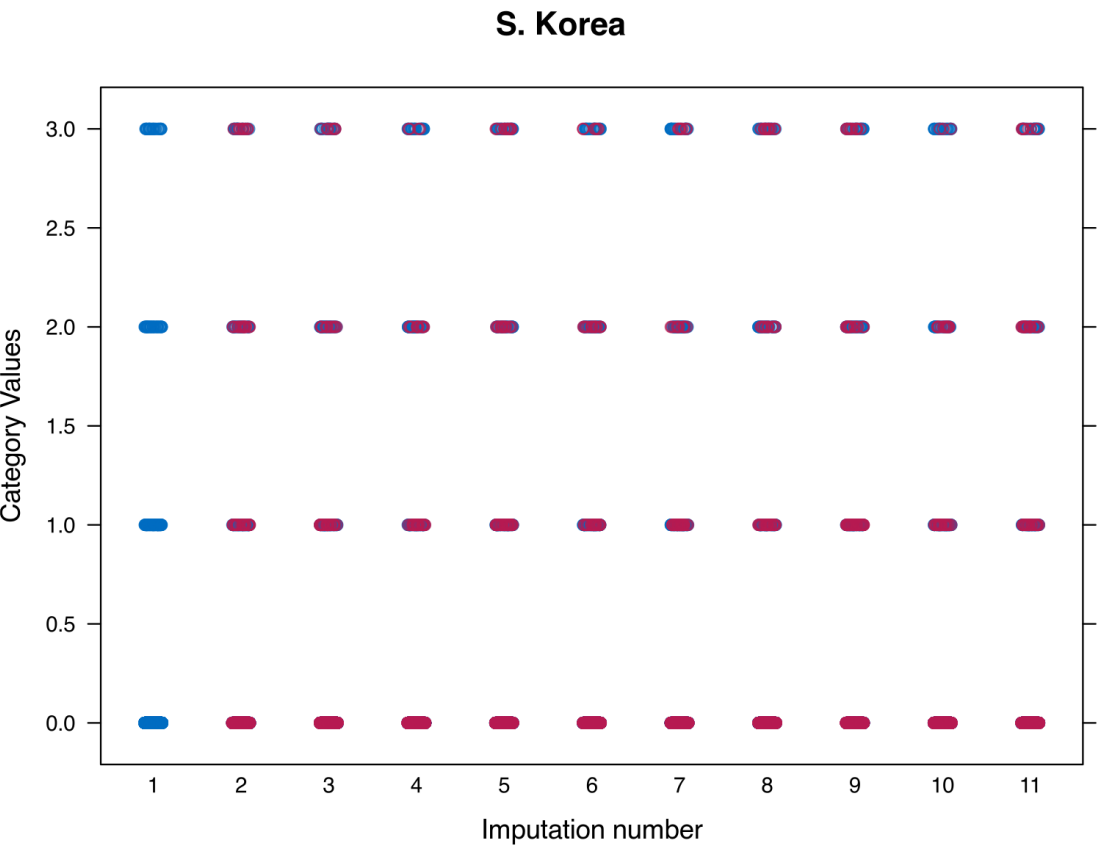
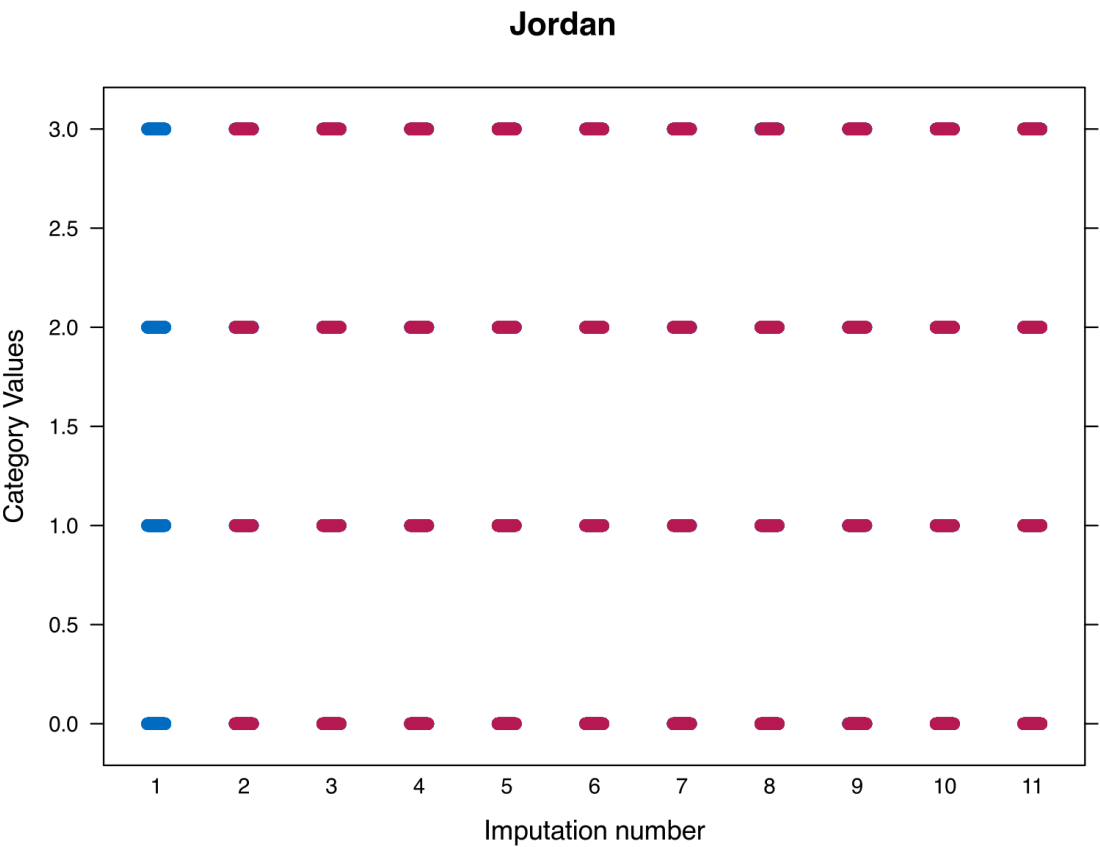


Exhibit C.5: Strip Plots for Absenteeism Predictor (Continued)

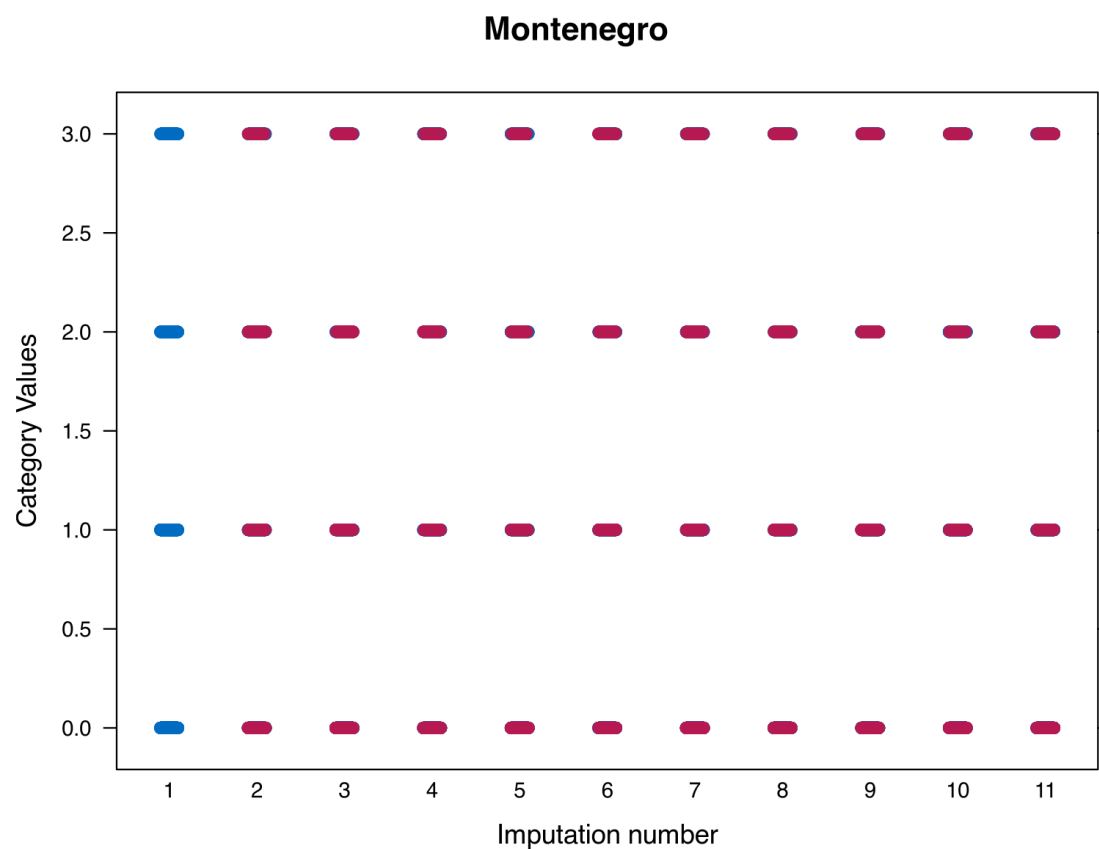
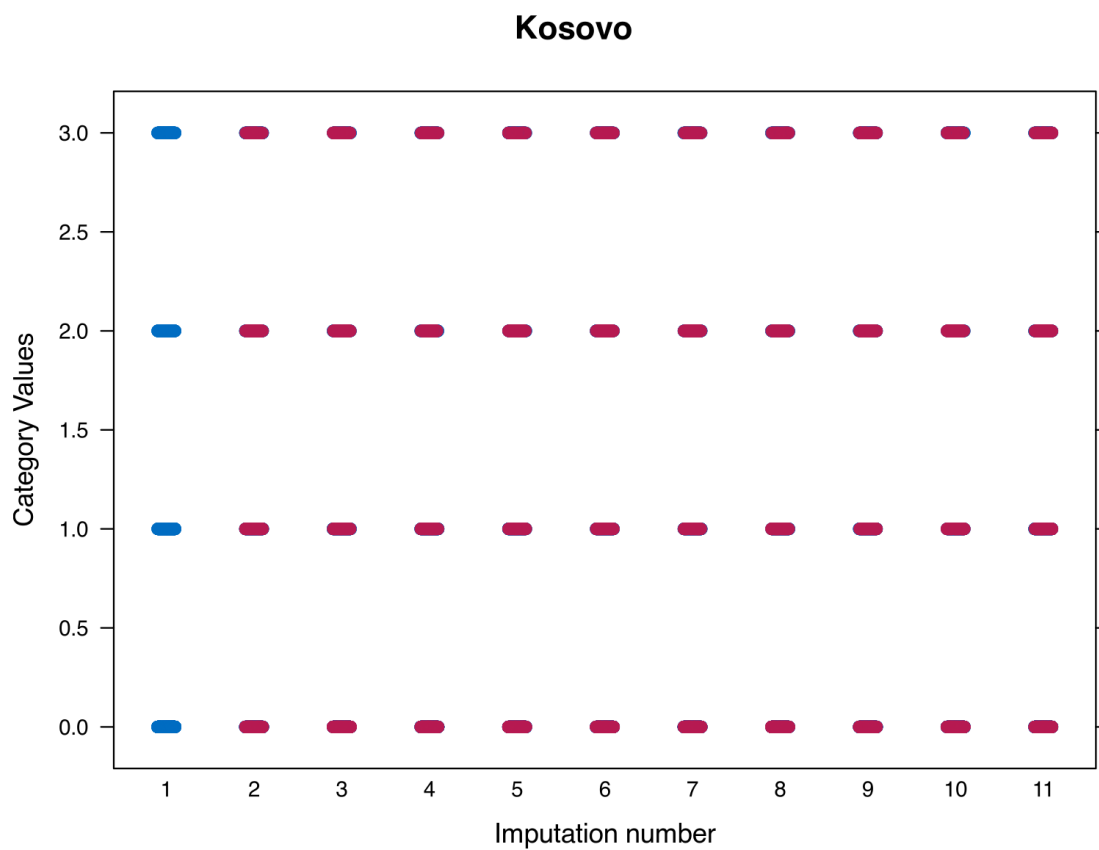
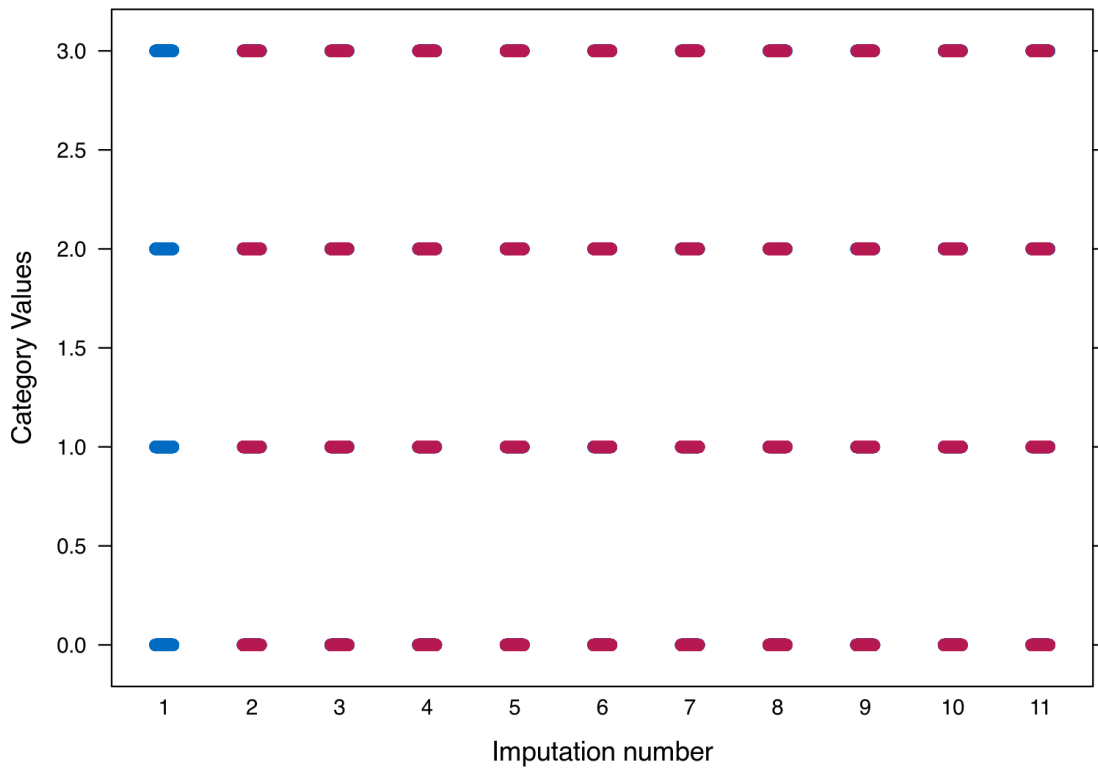


Exhibit C.5: Strip Plots for Absenteeism Predictor (Continued)

N. Macedonia



Slovenia

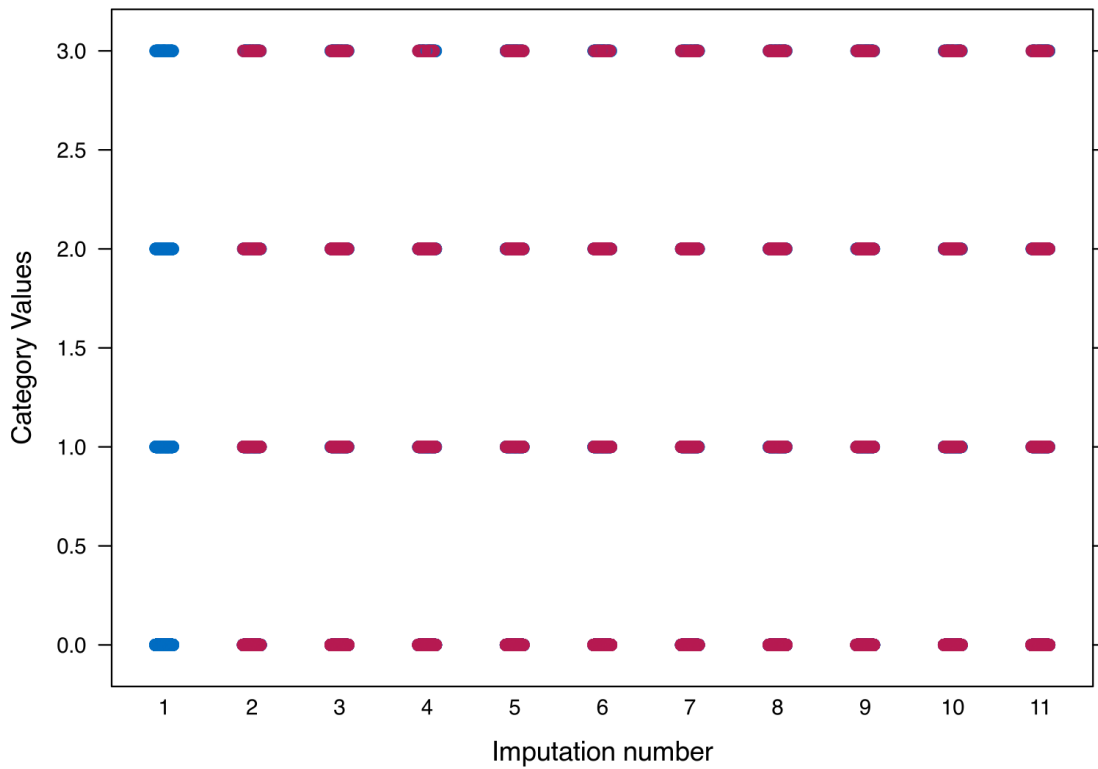


Exhibit C.5: Strip Plots for Absenteeism Predictor (Continued)

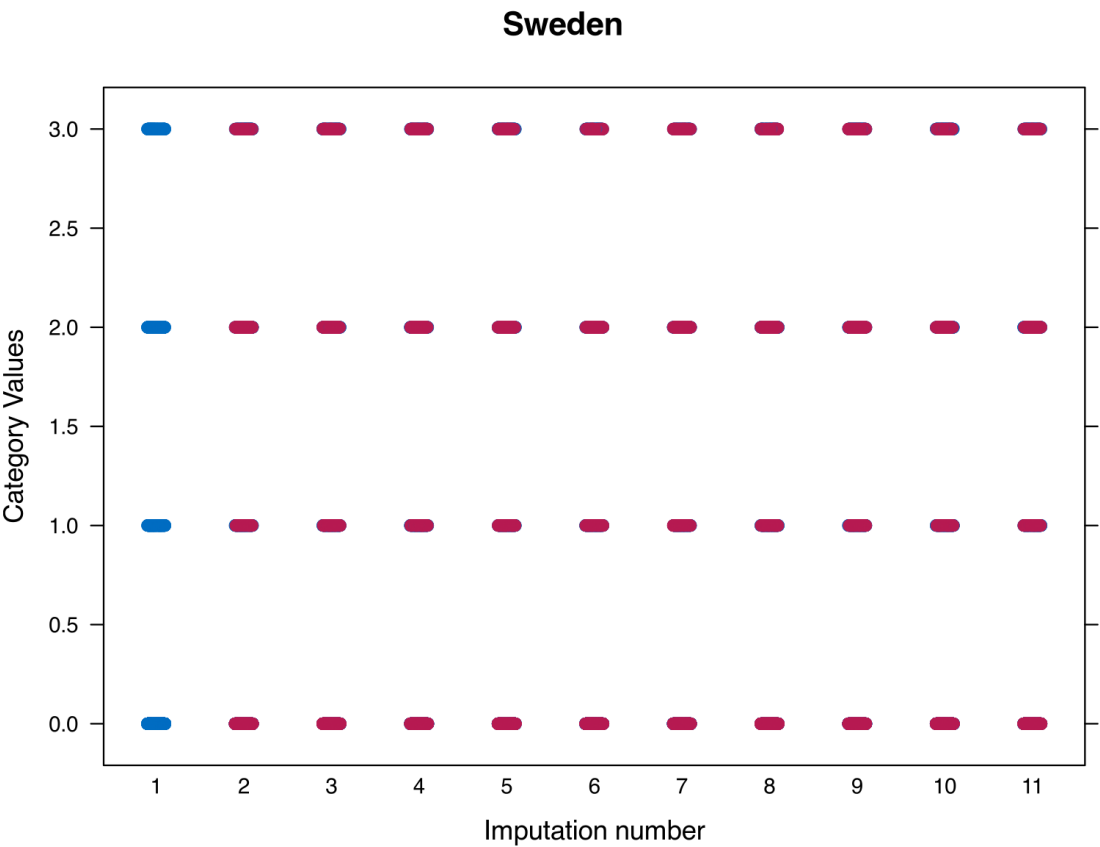


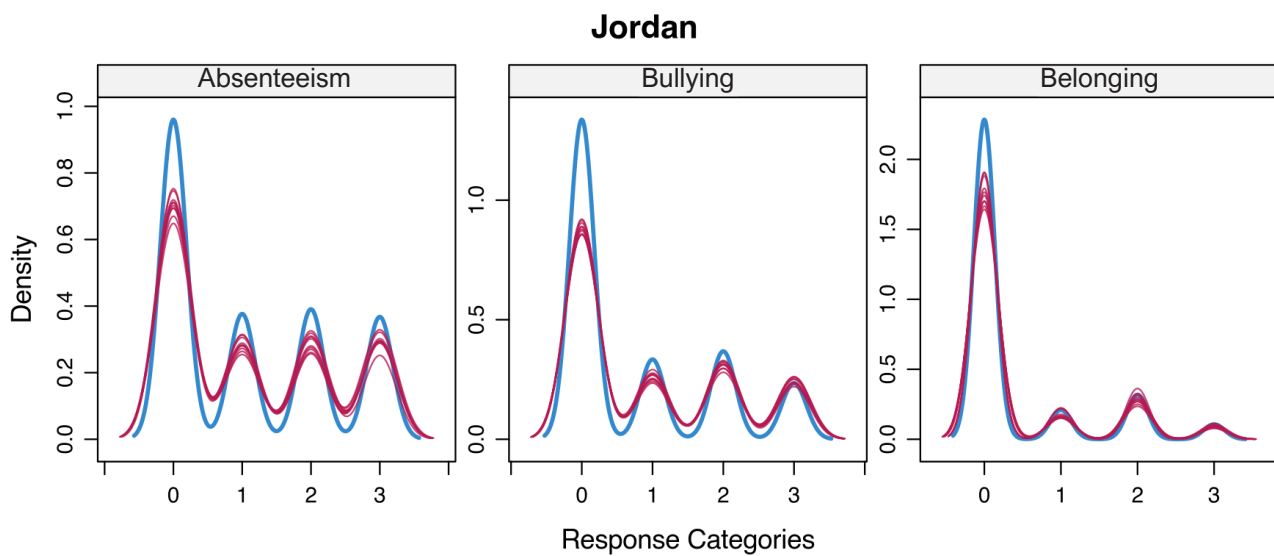
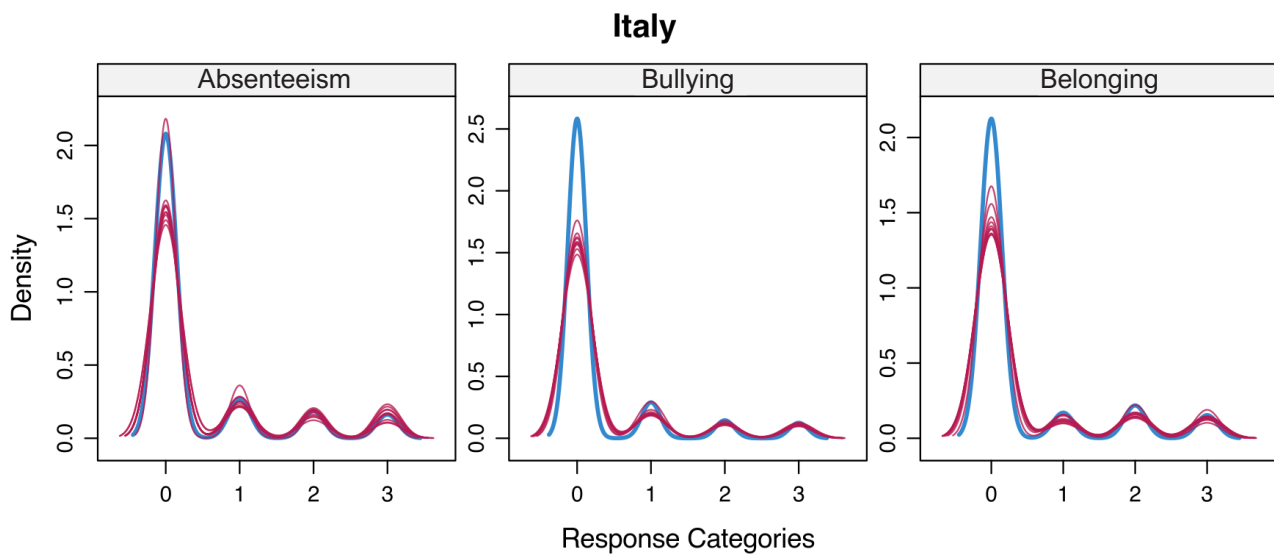
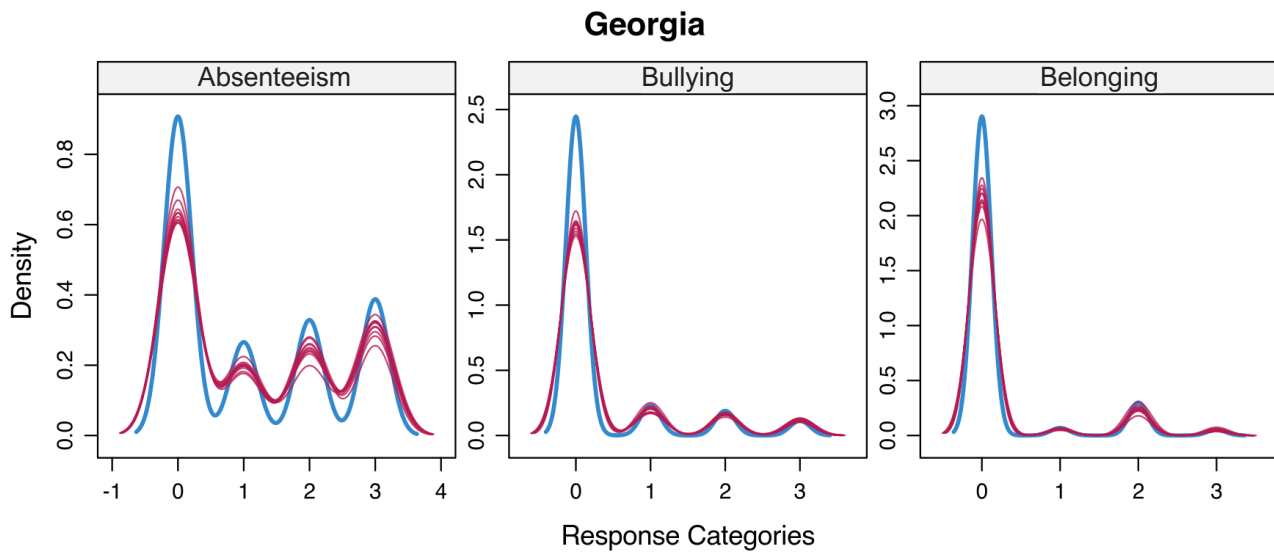
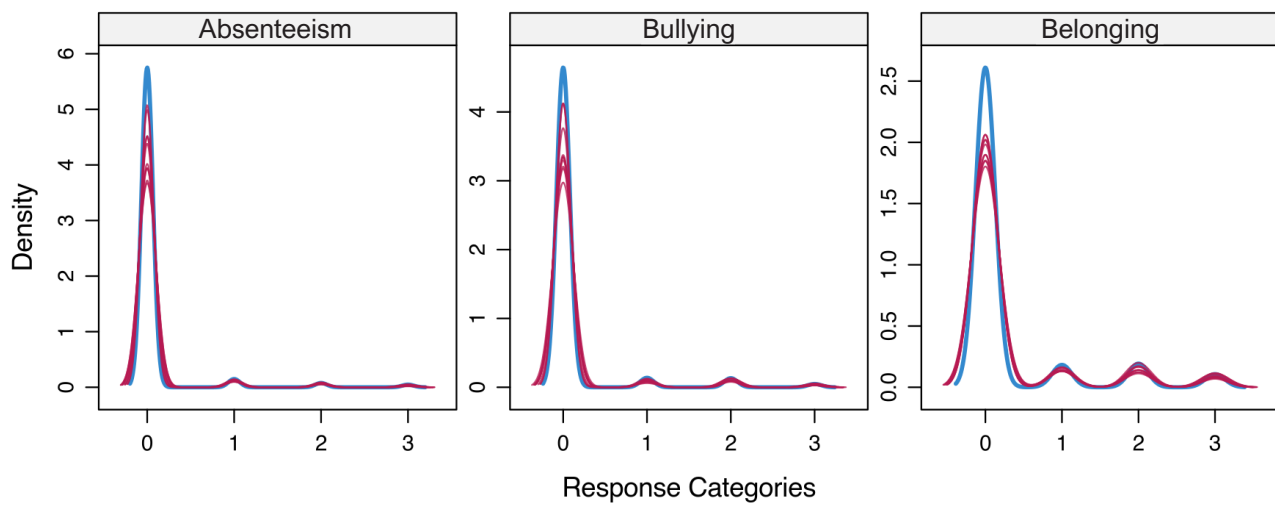
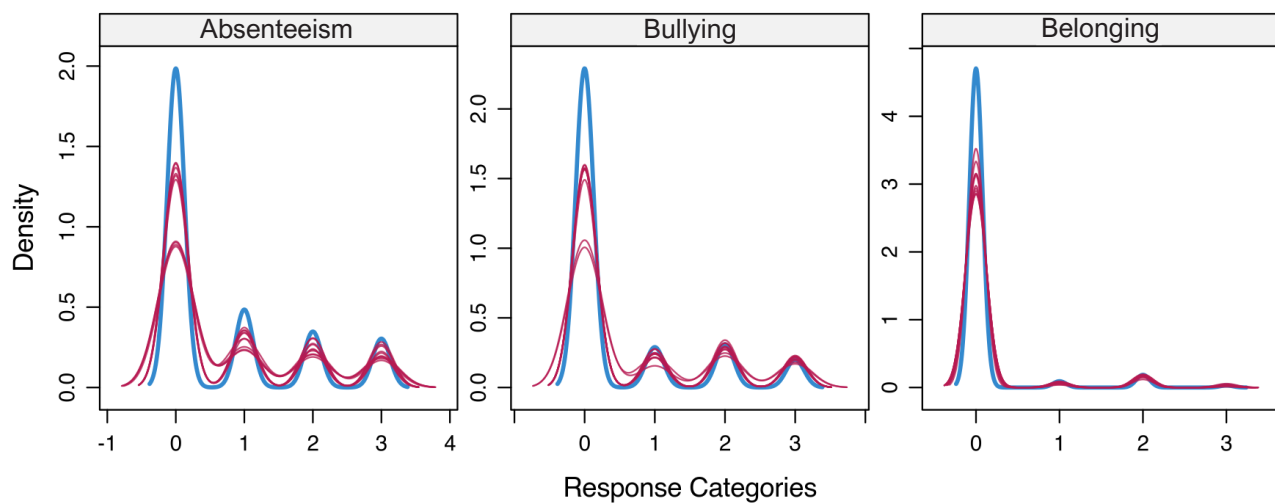
Exhibit C.6: Density Plots for Absenteeism, Bullying, and Belonging Predictors

Exhibit C.6: Density Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)

Korea, Rep. of



Kosovo



Montenegro

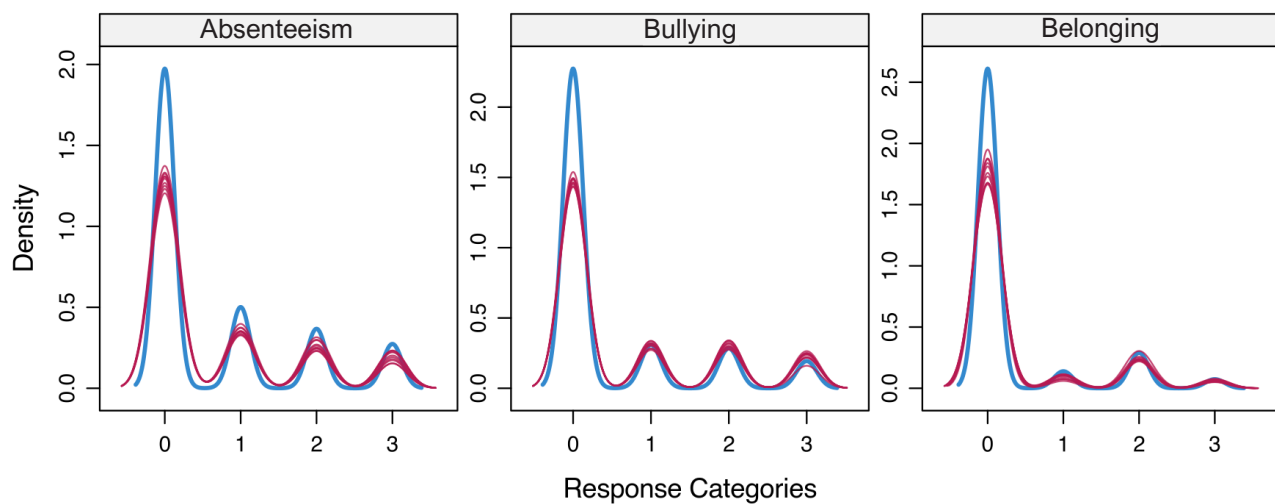
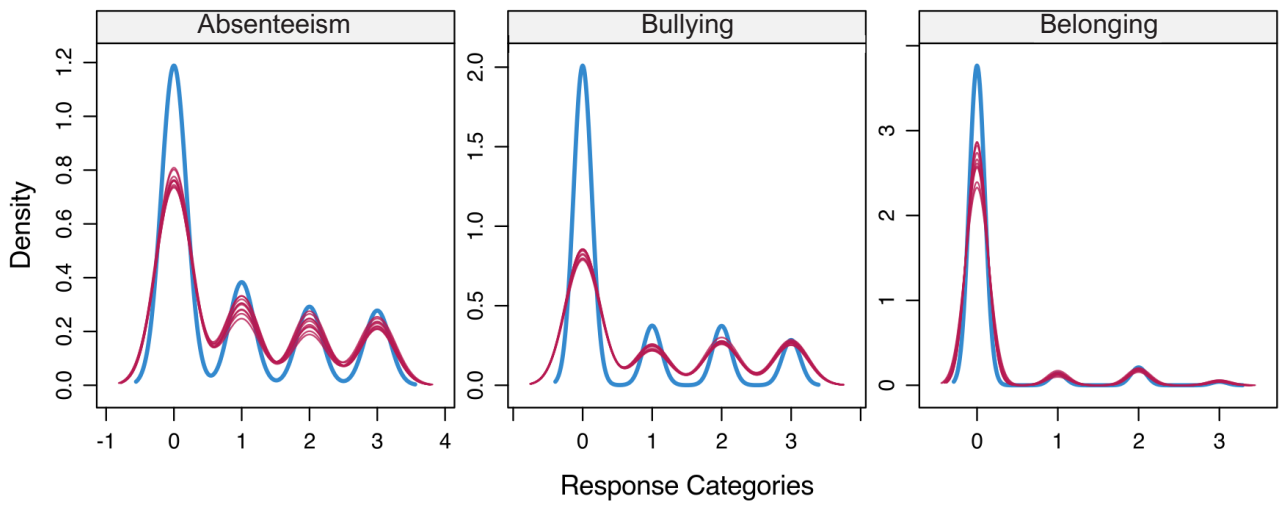
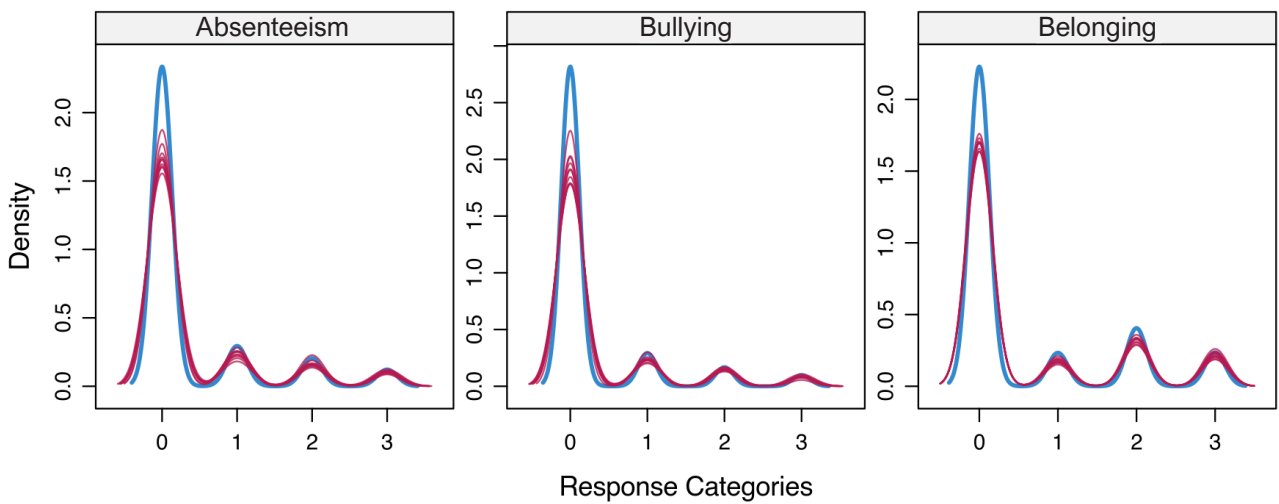
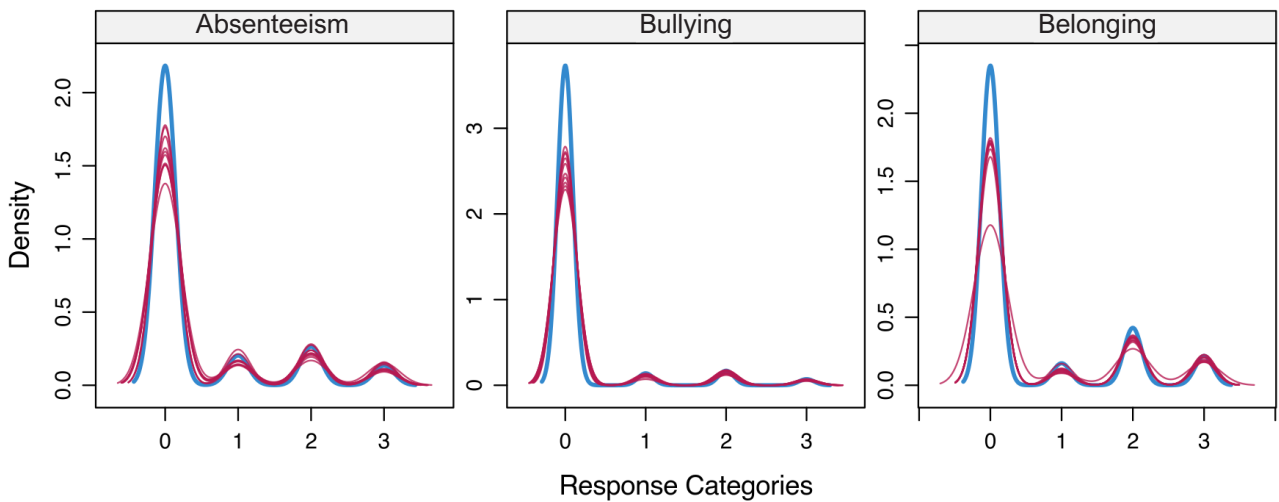


Exhibit C.6: Density Plots for Absenteeism, Bullying, and Belonging Predictors (Continued)**North Macedonia****Slovenia****Sweden**

Variable Centering

After imputation, three dummy variables were created from the four-level multicategorical predictor variables, and then centered within schools (i.e., “group-mean centering”). For each school j , a student’s i ’s value x_{ij} on a Level-1 predictor was transformed to $x_{ij} - \bar{x}_j$, the deviation from that school’s mean. Under this specification, a value of zero indicates a student at their own school’s average on that predictor, and the school-level random intercept captures between school differences in the outcome after accounting for the predictors included in the model. After group-mean centering, level-1 regression coefficients are interpreted as within-school associations. That is, the absenteeism coefficients reflect how and to what extent students in the same school, who are otherwise similar on prior achievement, home socioeconomic status (SES), climate, instructional clarity, and confidence, differ in 2024 achievement depending on the level of reported absenteeism. This approach removes the influence of school-level compositional differences that uncentered predictors can inadvertently carry (e.g., schools with systematically higher absenteeism or lower SES). As a result, the Level-1 slopes reflect student-level relationships rather than a mixture of within- and between-school effects. However, it is worth noticing that they may still reflect confounding from unmeasured student-level factors.^{89,90,91,92,93,94,95}

Group-mean centering serves two purposes. First, it decomposes each predictor into a within-school component (student deviations from the school mean) and an orthogonal between-school component (school means). The model uses the within-school component at Level 1, so the fixed effects regression parameters are estimated as a pure level-1 estimate, independent of any level-2 influence, and are particularly relevant for within-cluster comparisons.^{96,97,98} Second, it improves the interpretability of the model. That is because, after centering, the intercept represents the expected 2024 achievement for students are average for their school on all student-level predictors. In the context of the current model specification, the focus is on the within-school effects captured by the centered Level-1 slopes, while broader between-school differences are summarized by the random intercept variance (ICC).^{99,100,101,102}

HLMs Formalization

A series of two-level linear mixed models with students i nested in schools j were estimated to evaluate the association between absenteeism and mathematics and science achievement. The first model (Baseline Model) included only prior-year (Grade 4) achievement as predictor of Grade 5 achievement to account for the within-subject variability from one year to the next. In a second model (Absenteeism Only), student-reported absenteeism variables were included in addition to Grade 4 achievement to evaluate its impact on achievement above and beyond the role of prior year academic achievement. A third model (Full Model) included parent-reported home socioeconomic status and student-reported frequency of bullying experiences, sense of school belonging, instructional clarity in mathematics or science lessons, and confidence in mathematics or science. The purpose of this final model was to evaluate the impact of absenteeism after accounting for differences in students’ school experiences. All predictors, except for home SES, were entered in the model as a set of dummy-coded variables following the same coding scheme that identifies the prevalence of the predictor across both years (e.g., rare bullying in both years, frequent bullying only in Grade 4, frequent bullying only in Grade 5, frequent bullying in both grades).

Sampling weights were applied when estimating the models. Specifically, conditional student weights (TOTWGT/SCHWGT) were applied at level 1 and School Weights (SCHWGT) at level 2.

In TIMSS 2023, the student final weight (TOTWGT) refers to the student's inverse probability of being included in the TIMSS sample through the entire multistage sampling process (school, classes, and students), while the school weight (SCHWGT) refers to the inverse probability that a school was selected into the TIMSS sample. Given this, a conditional student weight defined as TOTWGT/SCHWGT isolates the student-level selection component conditional on the school having already been selected.^{103,104,105} All models were estimated in R, using the WeMix package.¹⁰⁶ Formalization of the Full Model is shown in Exhibit C.7. The outcome Y_{ij} is the 2024 achievement score (mathematics or science, depending on the section). At Level 1 (students), the model includes the first plausible value for prior achievement in the same subject (ASMMAT11 or ASSSCI11).ⁱ In addition, all the models included the household SES index (ASBHSES), three dummy indicators for frequent absenteeism (absent in 2023 only; in 2024 only; in both years), and three groups of risk indicators—frequent bullying, no/low sense of belonging, low subject-specific confidence, and low subject-specific instructional clarity, each coded with the same three dummies (report in 2023 only; report in 2024 only; report in both years). The omitted/reference category for each risk construct can be defined in a general way as “not in a risk condition in either year.” At Level 2 (schools), models include a random intercept (u_{0j}) to capture unobserved, potential school-specific influences (e.g., leadership, peer climate, resources) not addressed by student covariates fixed effects. The student residuals and the school random intercepts $u_{0j} \sim N(0, \sigma^2)$ are assumed independent.

i Only the first plausible value (PV1) for prior achievement was used as a covariate in all model estimations. This analytical shortcut was adopted to reduce computational burden because multilevel multiple imputation was required for the background variables.

Exhibit C.7: HLM Formalization**Level 1: Students (i in school j)**

$$\begin{aligned}
Y_{ij} = & \beta_{0j} + \beta_1 \text{2023_Achievement}_{ij}^{\text{cwc}} + \beta_2 \text{ASBHSES}_{ij}^{\text{cwc}} \\
& + \beta_3 \text{FrequentAbsence_2023only}_{ij}^{\text{cwc}} + \beta_4 \text{FrequentAbsence_2024only}_{ij}^{\text{cwc}} + \beta_5 \text{FrequentAbsence_BothYears}_{ij}^{\text{cwc}} \\
& + \beta_6 \text{FrequentBullying_2023only}_{ij}^{\text{cwc}} + \beta_7 \text{FrequentBullying_2024only}_{ij}^{\text{cwc}} + \beta_8 \text{FrequentBullying_BothYears}_{ij}^{\text{cwc}} \\
& + \beta_9 \text{LittleSenseBelonging_2023only}_{ij}^{\text{cwc}} + \beta_{10} \text{LittleSenseBelonging_2024only}_{ij}^{\text{cwc}} + \beta_{11} \text{LittleSenseBelonging_BothYears}_{ij}^{\text{cwc}} \\
& + \beta_{12} \text{NotConfident_2023only}_{ij}^{\text{cwc}} + \beta_{13} \text{NotConfident_2024only}_{ij}^{\text{cwc}} + \beta_{14} \text{NotConfident_BothYears}_{ij}^{\text{cwc}} \\
& + \beta_{15} \text{LowInstructionalClarity_2023only}_{ij}^{\text{cwc}} + \beta_{16} \text{LowInstructionalClarity_2024only}_{ij}^{\text{cwc}} + \beta_{17} \text{LowInstructionalClarity_BothYears}_{ij}^{\text{cwc}} \\
& + e_{ij}
\end{aligned}$$

with residual error:

$$e_{ij} \sim N(0, \sigma_e^2)$$

Level 2: Schools (school j)

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

with school-level random effect:

$$u_{0j} \sim N(0, \sigma_u^2)$$

Combined Mixed-Effects Model

$$Y_{ij} = \gamma_{00} + \sum_{p=1}^{17} \gamma_{p0} X_{p,ij}^{(\text{cwc})} + u_{0j} + e_{ij}$$

Notation

- **Indices**
 - i : student
 - j : school
- **Outcome Variable**
 - Y_{ij} : TIMSS mathematics score (ASMMAT21) for student i in school j
- **Predictors**
 - $X_{p,ij}^{(\text{cwc})}$: the p -th student-level predictor, centered within school
- **Fixed Effects**
 - γ_{p0} : fixed slope for the p -th predictor (average effect across all schools)
 - γ_{00} : grand mean intercept (predicted score for an “average” student in an “average” school)
- **Random Effects**
 - β_{0j} : school-specific intercept
 - u_{0j} : school-level random intercept (school j ’s deviation from the grand mean γ_{00})
 - * $u_{0j} \sim N(0, \sigma_u^2)$
- **Error Term**
 - e_{ij} : student-level residual (student i ’s deviation from their school prediction)
 - * $e_{ij} \sim N(0, \sigma_e^2)$
- **Variance Components**
 - σ_u^2 : variance of school-level intercepts (between-school variance)
 - σ_e^2 : variance of student-level residuals (within-school variance)

HLMs Estimates Pooling

The weighted multilevel model parameter pooling process was performed using a two-stage approach: first, pooling regression parameters across 10 imputed datasets for each plausible value of each outcome (mathematics and science), then, pooling across the five plausible value estimates. Pooling was conducted separately for each country using Rubin's rules as detailed below.^{107,108}

For the present procedures, the following terms are defined:

- $k=1, \dots, K$: index plausible values, PVs, ($K=1, \dots, 5$)
- $m=1, \dots, M$: index multiple imputations created for missing data ($M=1, \dots, 10$)
- $\hat{Q}_{km}$: estimated model fixed-effects parameter multilevel model to PV k and imputation m .
- $\hat{U}_{km}$: estimated variance of $\hat{Q}_{km}$

Stage 1: Pooling across Multiple Imputations

In the first stage, the HLM model was estimated for each Plausible Value (PV) on 10 imputed datasets. For a fixed PV k , the same HLM model is fitted to each of the M imputed datasets. Results were then combined into a single pooled estimate for PV k using Rubin's rules. Under this framework the pooled point estimate within PV k is defined as

$$\bar{Q}_k = \frac{1}{M} \sum_{m=1}^M \hat{Q}_{km}$$

Similarly, the within-imputation variance within PV k can be defined as

$$\bar{U}_k = \frac{1}{M} \sum_{m=1}^M \hat{U}_{km}$$

and can be interpreted as the average of the estimated variances (squared SEs) from each imputed dataset. The latter captures the typical model-estimation variance given a completed dataset.

Furthermore, the between-imputation variance within PV k is defined as

$$B_k = \frac{1}{M-1} \sum_{m=1}^M (\hat{Q}_{km} - \bar{Q}_k)^2$$

and can be understood as how much the coefficient estimates changes across imputations, which captures imputation uncertainty due to missing covariates.

Lastly, the total variance within PV k is defined as

$$T_k = \bar{U}_k + \left(1 + \frac{1}{M}\right) B_k$$

and represents the pooled variance for PV k , combining within-imputation variance with the additional uncertainty introduced from having only M imputations. This is the variance underlying the standard error reported by common tools such as the `r mice::pool()` tool.¹⁰⁹

Stage 2: Pooling across Plausible Values

After Stage 1, K pooled estimates $\bar{Q}_k$ (one per PV) and their respective variances T_k are available. Stage 2 pooling combines these across PVs to incorporate latent proficiency uncertainty represented by the multiple plausible values. The following terms are defined:

- $Q_k := \bar{Q}_k$ (Stage 1 pooled estimate for PV k)
- $T_k := \bar{T}_k$ (Stage 1 pooled variance for PV k)

Then, the overall pooled point estimate across PVs is defined as

$$\bar{Q} = \frac{1}{K} \sum_{k=1}^K Q_k$$

and provides the final reported coefficient that represents the average of the PV-specific pooled coefficients. Then, the average within-PV variance can be defined as

$$\bar{U} = \frac{1}{K} \sum_{k=1}^K U_k$$

and refers to the average of the variances from the Stage 1 pooled results, which reflects model-estimation variance plus MI uncertainty (because $U_k = T_k$ already includes both). Between-PV variance, which portrays measurement uncertainty, is defined as

$$B = \frac{1}{K-1} \sum_{k=1}^K (Q_k - \bar{Q})^2$$

and provides information about how much the pooled coefficient changes across plausible values. The latter is meant to capture the uncertainty introduced due to drawing different plausible proficiencies from the posterior distribution. Lastly, the total variance across PVs is expressed as

$$T = \bar{U} + \left(1 + \frac{1}{K}\right) B$$

and is the final variance component used for statistical inference as it combines within-PV variance ($\bar{U}$) and the additional uncertainty introduced by PVs B , with a finite- K correction $(1+1)/K$. Based on this, the final standard error is expressed as

$$SE(\bar{Q}) = \sqrt{T}$$

Finally, Rubin-style degrees of freedom (ν) were used for statistical inference, defined as follows:

$$\nu \approx (K-1) \left(1 + \frac{\bar{U}}{\left(1 + \frac{1}{K}\right) B} \right)^2$$

The two-stage pooling process described above targets the measurement uncertainty and also incorporates uncertainty due to the multiple imputation of missing covariates inside $\bar{U}$. This is because the Stage 1 pooled variances ($U_k = T_k$) already reflect imputation uncertainty.

The standard errors in this report do not fully incorporate TIMSS complex-sampling variance due to the absence of jackknife repeated replication weights. When parameters are not re-estimated using replicate weights, the variance of means is underestimated, even with large samples.¹¹⁰ Future research should explore how this additional design-based variance can be incorporated into the two-stage pooling procedure. For the time being, however, this report refrains from assessing statistical significance in a strict inferential sense. Instead, researchers should compare the estimated regression coefficients directly and look for converging patterns across countries. Consistent substantive findings—for example, similar magnitudes and directions of the absenteeism coefficients across multiple education systems—would provide more reliable evidence than a narrow focus on p -values, which may be misleading under incomplete variance estimation.

Full HLM Results

Exhibits C.8 and C.9 show the full HLM model results for the mathematics and science models, respectively.

Exhibit C.8: Full Model Results – Mathematics

Coefficient	Georgia		Italy		Jordan		Korea, Rep. of		Kosovo		Montenegro		North Macedonia		Slovenia		Sweden	
	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*
Intercept	518.86	3.63	551.47	3.15	434.96	4.31	634.47	2.55	467.51	3.89	492.04	3.11	488.80	4.18	555.19	1.94	559.79	2.74
Grade 4 (2023) Mathematics Achievement	0.74	0.03	0.76	0.02	0.61	0.02	0.84	0.04	0.76	0.03	0.67	0.03	0.63	0.03	0.78	0.03	0.78	0.04
Home Socioeconomic Status	3.22	0.65	2.69	0.62	5.33	0.81	1.27	0.95	1.56	0.95	5.36	0.88	4.87	0.99	2.66	0.81	3.17	0.70
Frequent Absence, 2023 Only	-7.07	3.11	-2.82	3.51	-7.30	3.56	-5.09	5.61	-2.69	3.13	-2.70	2.94	-9.18	3.03	-3.51	2.77	0.23	3.13
Frequent Absence, 2024 Only	-8.50	2.54	-2.39	2.99	-9.02	3.37	-9.31	6.21	-8.48	3.67	-12.14	3.03	-16.43	3.20	-5.30	2.95	-4.48	2.28
Frequent Absence in Both Years	-11.94	2.80	-5.60	4.12	-13.35	3.20	-13.40	9.48	-8.45	3.41	-11.23	3.29	-15.98	3.84	-5.28	3.89	-3.44	3.57
Frequent Bullying, 2023 Only	-4.18	3.77	-0.77	3.24	-3.29	3.44	0.77	5.22	1.45	4.26	-8.23	3.42	-2.20	3.46	1.00	2.92	-5.37	4.17
Frequent Bullying, 2024 Only	-14.57	4.51	-3.10	3.56	-15.14	4.04	-0.73	4.76	-6.12	2.89	-25.12	2.95	-15.86	3.33	-9.52	3.78	-8.91	4.17
Frequent Bullying, Both Years	-10.60	4.77	-11.04	5.02	-13.92	4.69	-25.79	8.04	-5.29	4.53	-22.29	4.78	-13.60	4.77	-3.41	4.23	-14.51	5.73
Little Sense of School Belonging, 2023 Only	6.70	7.20	5.43	3.46	-4.38	4.59	-2.18	4.31	-13.30	8.62	2.05	4.75	-3.33	8.21	5.84	2.90	3.57	3.92
Little Sense of School Belonging, 2024 Only	-1.67	4.08	-0.85	3.80	-0.70	4.09	-0.62	3.88	0.03	5.28	-7.14	3.58	-3.87	5.29	-0.52	2.31	1.32	2.67
Little Sense of School Belonging, Both Years	17.84	8.86	1.55	3.81	-1.56	6.17	-2.20	4.85	-8.90	16.20	1.37	6.12	-9.07	10.90	0.95	2.75	1.80	3.83
Not Confident in Mathematics, 2023 Only	-8.25	4.22	-9.44	2.85	-12.41	3.07	1.05	3.02	-14.72	3.15	-8.18	3.29	-12.87	3.41	-7.71	2.60	-3.07	3.20
Not Confident in Mathematics, 2024 Only	-7.65	3.48	-18.72	2.27	-8.64	3.07	-3.92	2.72	-13.91	2.82	-15.26	2.87	-16.13	3.17	-12.59	2.43	-17.52	2.76
Not Confident in Mathematics, Both Years	-14.68	3.68	-18.81	2.81	-15.41	3.61	-4.08	2.51	-18.75	3.16	-13.72	3.47	-20.82	3.53	-13.69	2.54	-13.59	3.00
Low Clarity of Mathematics Instruction, 2023 Only	-4.68	8.81	-6.15	5.66	-9.92	5.12	-6.35	4.39	-10.28	6.79	-6.47	6.50	-10.53	7.05	7.27	4.82	-5.58	4.04
Low Clarity of Mathematics Instruction, 2024 Only	0.12	6.06	-9.27	3.63	-13.31	5.93	-3.94	4.05	-18.20	6.53	-10.01	4.39	-11.38	8.23	-7.62	3.17	-8.15	3.46
Low Clarity of Mathematics Instruction, Both Years	-48.69	27.49	2.11	7.21	-3.70	13.17	16.44	11.17	-14.60	18.57	-10.53	14.73	-24.63	19.34	-5.89	7.66	-10.78	5.26

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system.
See Estimates Pooling in Appendix C for further details.

Exhibit C.9: Full Model Results – Science

Coefficient	Georgia		Italy		Jordan		Korea, Rep. of		Kosovo		Montenegro		North Macedonia		Slovenia		Sweden	
	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*	Estimate	S.E.*
Intercept	487.19	3.73	543.20	2.96	432.77	4.51	616.15	2.11	422.57	3.44	479.51	3.36	449.01	4.27	562.41	1.83	560.56	3.22
Grade 4 (2023) Science Achievement	0.73	0.05	0.75	0.04	0.69	0.04	0.82	0.05	0.68	0.05	0.69	0.04	0.61	0.04	0.73	0.04	0.75	0.06
Home Socioeconomic Status	5.92	0.95	3.09	0.64	4.05	0.87	1.91	1.14	1.72	0.90	4.47	0.90	4.32	1.04	2.78	1.13	3.75	0.85
Frequent Absence, 2023 Only	-7.12	3.80	-1.78	2.71	-6.46	3.15	-4.64	7.22	-7.08	3.32	-2.88	3.18	-5.37	2.83	-5.67	2.56	-4.26	4.51
Frequent Absence, 2024 Only	-9.84	3.22	0.39	3.73	-7.56	3.49	-10.20	6.69	-13.93	3.50	-12.24	2.83	-15.92	3.00	-10.21	2.97	-7.07	2.73
Frequent Absence in Both Years	-11.02	2.63	1.78	3.38	-6.85	3.79	-8.34	9.39	-14.99	3.43	-12.64	3.47	-14.42	3.25	-10.41	4.49	-6.90	4.20
Frequent Bullying, 2023 Only	-4.34	4.32	1.64	2.62	-1.99	3.62	-7.09	4.53	-3.40	3.60	-3.19	3.84	-1.58	3.69	-4.23	3.07	1.49	4.60
Frequent Bullying, 2024 Only	-19.00	5.39	-7.07	4.42	-5.05	3.64	-4.19	4.29	-10.06	3.39	-24.36	3.17	-15.29	3.26	-13.94	3.47	-1.49	4.80
Frequent Bullying, Both Years	-13.54	5.39	-6.47	5.50	-6.46	5.14	-7.72	8.56	-10.73	4.86	-19.48	5.09	-17.13	3.80	-7.47	4.76	-4.62	6.15
Little Sense of School Belonging, 2023 Only	-0.29	6.49	1.48	2.91	-3.48	6.30	2.46	3.74	1.96	10.66	1.35	4.33	-8.14	5.99	2.04	2.65	8.03	4.04
Little Sense of School Belonging, 2024 Only	0.51	4.51	-3.75	3.14	-4.70	4.33	3.39	2.85	4.86	5.02	-2.44	3.44	0.57	6.01	-5.60	2.38	-2.10	2.98
Little Sense of School Belonging, Both Years	13.00	7.41	-5.37	3.43	4.77	5.52	5.07	3.95	-16.32	11.80	-3.98	6.43	-6.75	10.73	-4.20	2.97	0.32	3.41
Not Confident in Science, 2023 Only	-0.80	3.45	-0.67	2.49	-9.18	3.06	-0.97	3.77	-9.45	2.95	-5.74	2.71	-4.64	3.21	-1.07	2.57	-4.83	2.94
Not Confident in Science, 2024 Only	-12.52	3.17	-7.94	2.92	-15.01	3.17	-8.48	2.42	-14.93	3.57	-13.54	2.82	-11.33	2.81	-6.78	2.71	-9.55	3.01
Not Confident in Science, Both Years	-8.59	3.43	-5.58	3.10	-18.74	4.63	-7.81	3.47	-15.07	3.80	-11.31	3.25	-12.86	3.27	-4.43	2.77	-8.04	3.89
Low Clarity of Science Instruction, 2023 Only	-2.96	7.01	1.28	4.47	-14.90	5.72	-3.90	3.57	-17.57	7.68	-2.62	7.14	-8.85	6.38	-3.73	4.87	-5.35	4.69
Low Clarity of Science Instruction, 2024 Only	-13.05	6.44	-7.87	3.40	-14.27	4.88	-3.85	3.54	-5.34	8.03	-8.52	5.02	-8.82	5.31	-6.93	3.45	-6.75	3.54
Low Clarity of Science Instruction, Both Years	-32.78	19.05	-9.62	6.95	-20.97	11.35	-2.07	10.76	-1.51	26.45	-17.22	14.49	-14.61	17.64	-3.86	7.47	-12.03	7.72

* Parameter estimates and cluster-robust standard errors from weighted models pooled using Rubin's rules across 10 imputations and 5 plausible values for each education system.
See Estimates Pooling in Appendix C for further details.

Comparison Between Complete-Case and Imputed Parameter Estimates (Full Models)

Exhibit C.9 and C.10 present graphical comparisons of the regression model parameters across the original data versus the imputed data (Full Models) created using the procedures detailed above. The results show that the parameters are, for the most part, comparable across the two data sets. Exceptions occur for unusually small groups (for example, there were very few students who reported low instructional clarity in mathematics for both assessment years in North Macedonia).

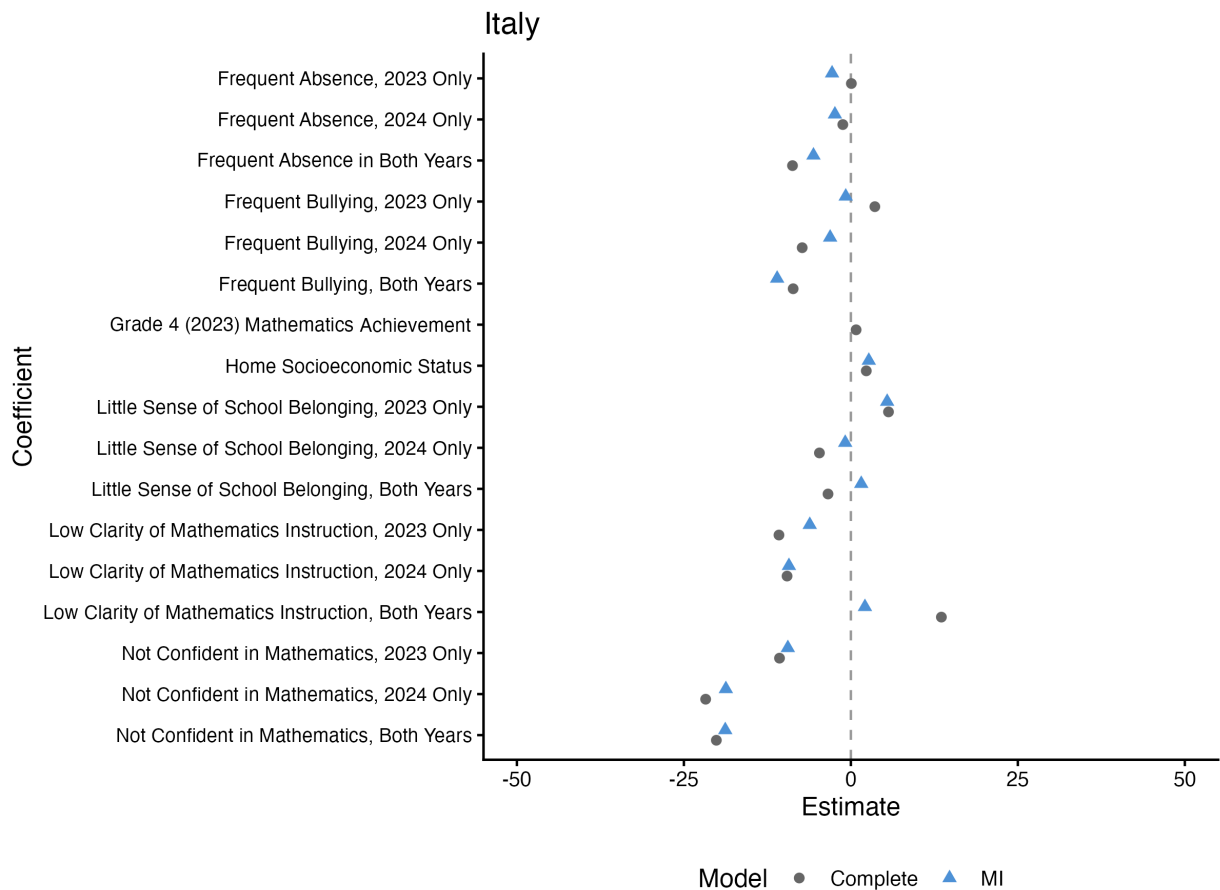
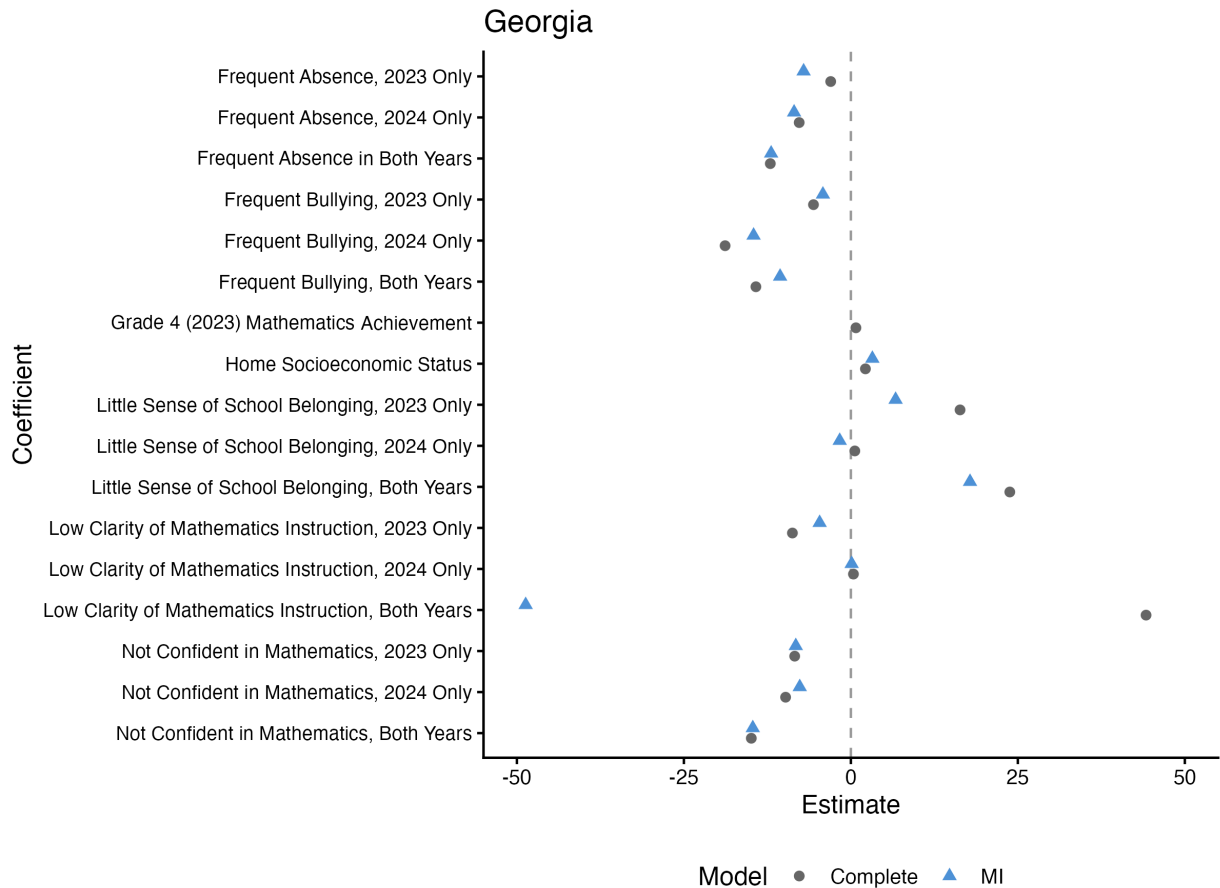
Exhibit C.10: HLM Estimates for Mathematics: Complete Cases versus Pooled MI Parameters

Exhibit C.10: HLM Estimates for Mathematics: Complete Cases versus Pooled MI Parameters (Continued)

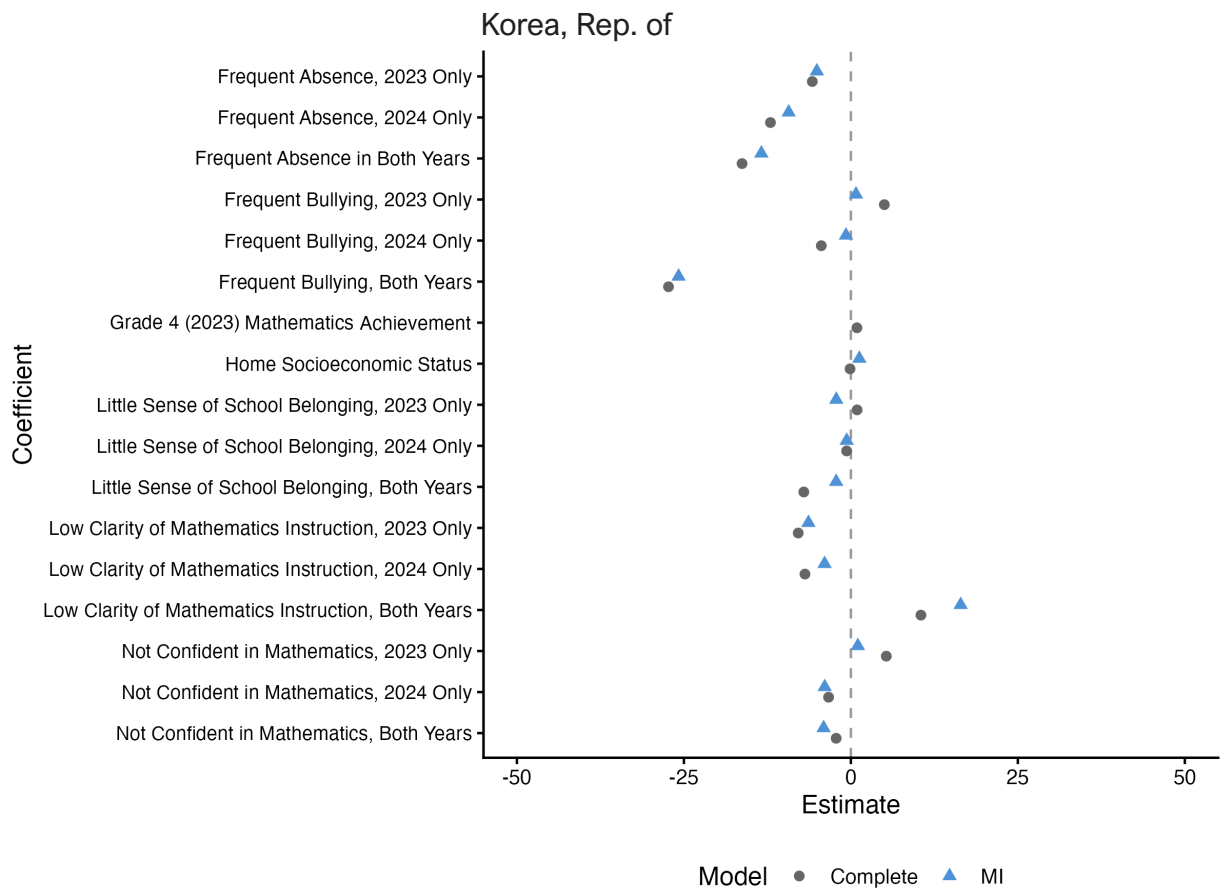
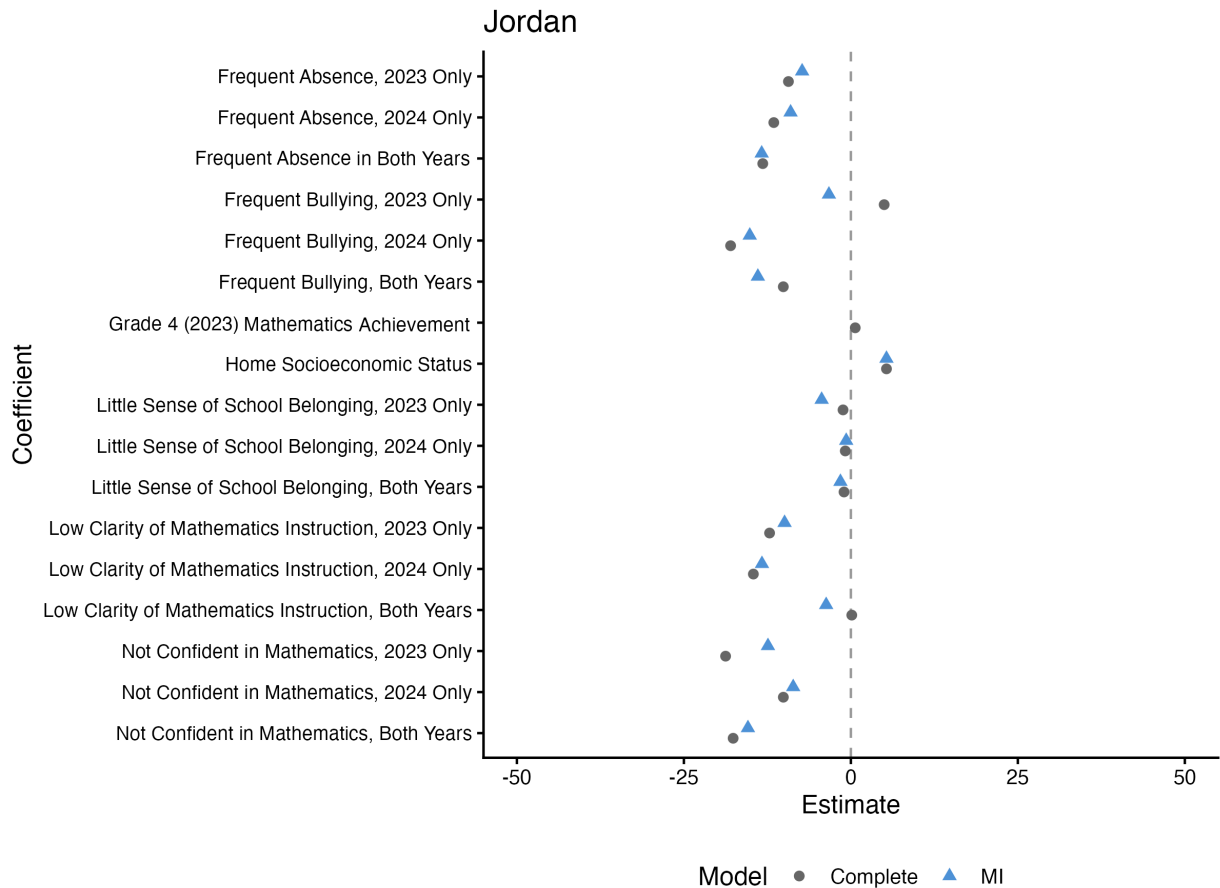


Exhibit C.10: HLM Estimates for Mathematics: Complete Cases versus Pooled MI Parameters (Continued)

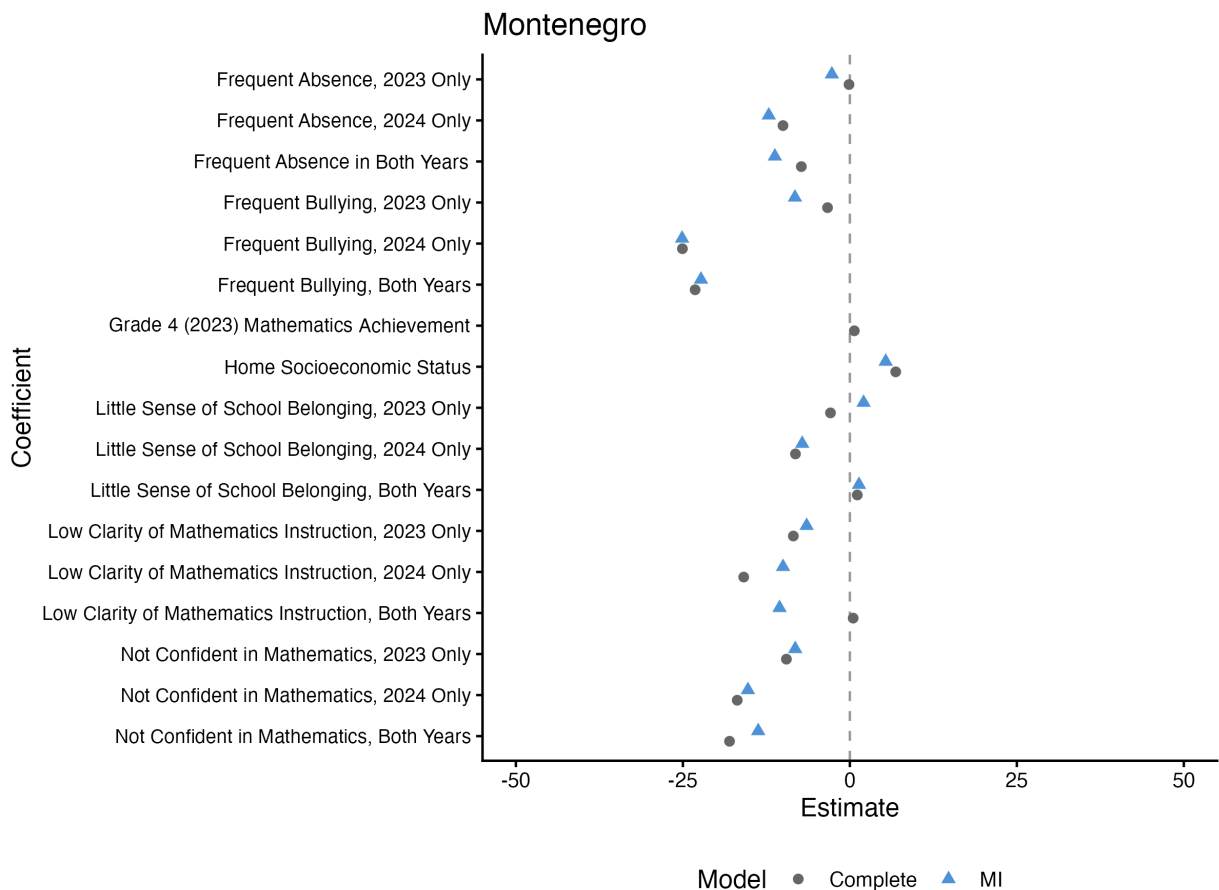
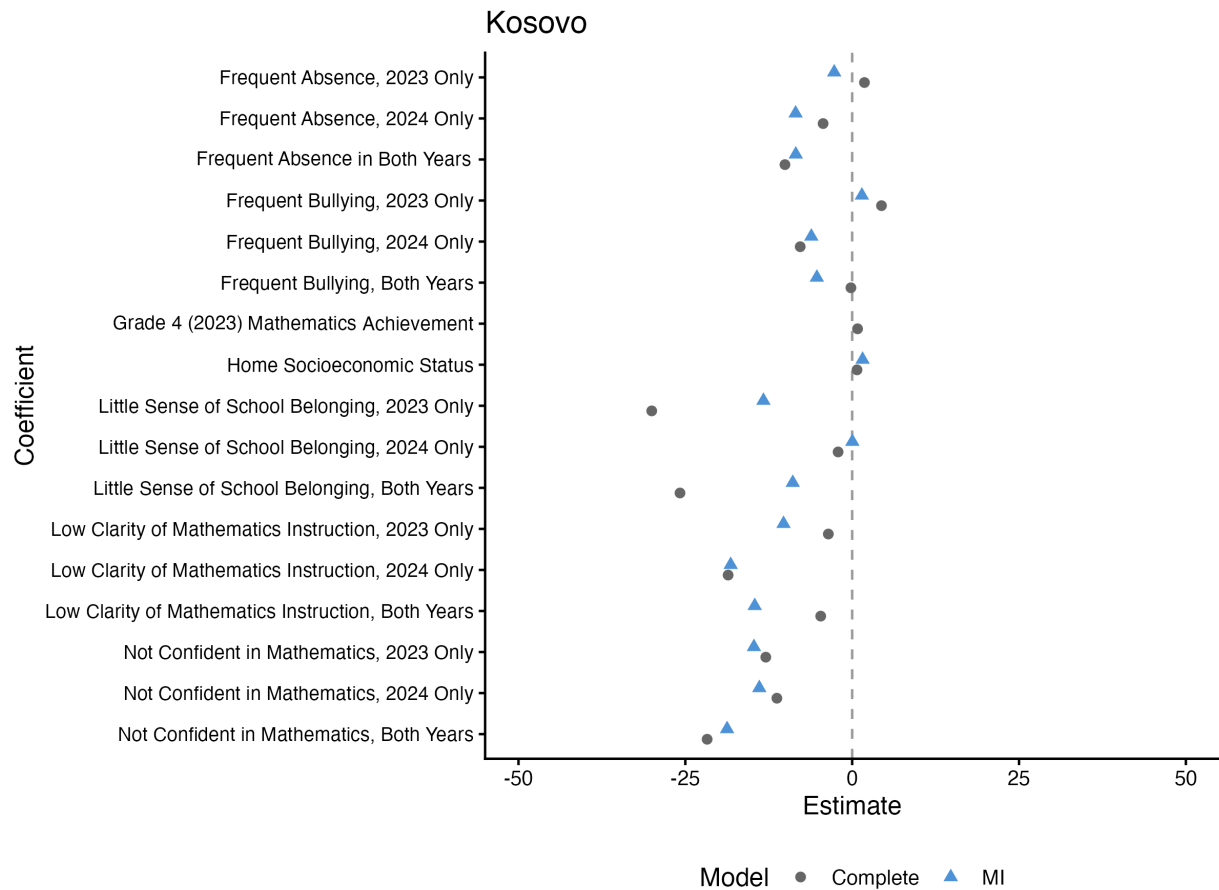


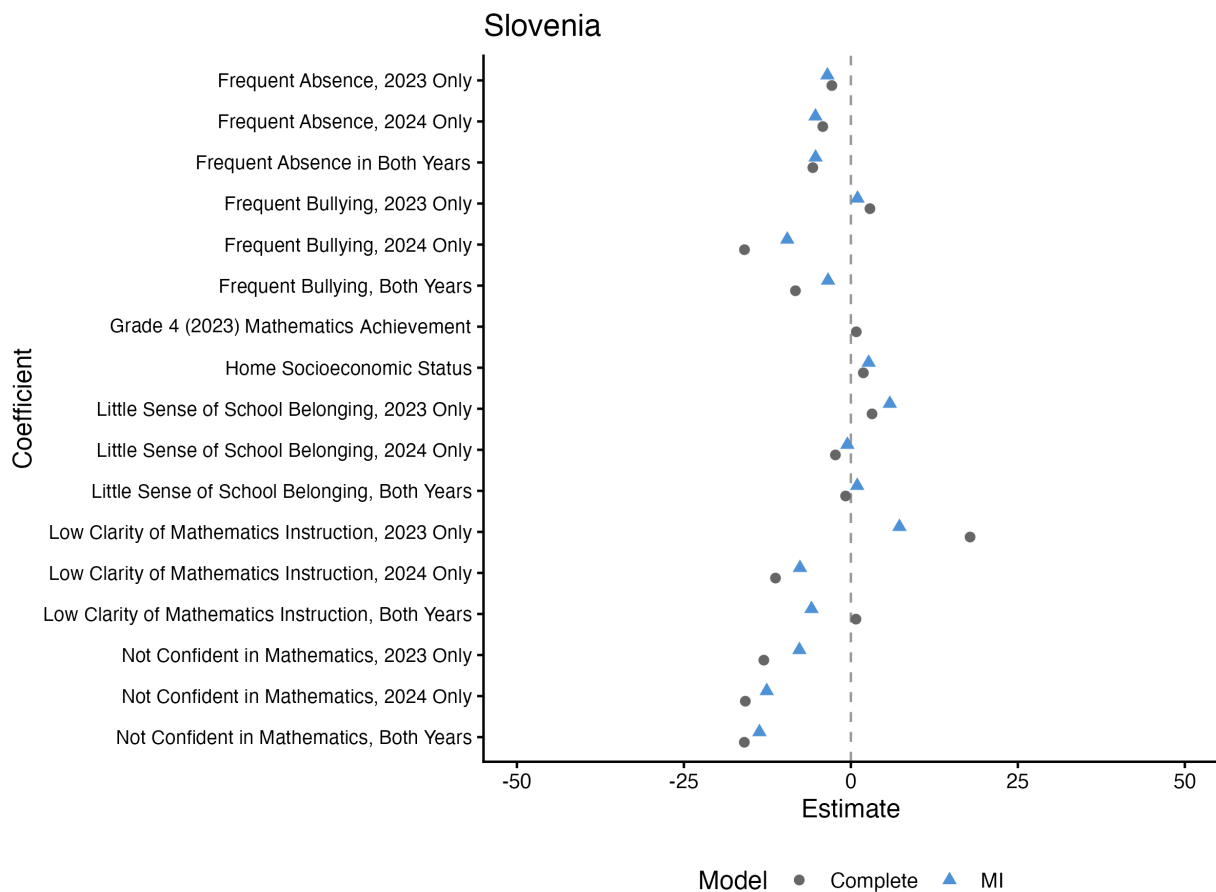
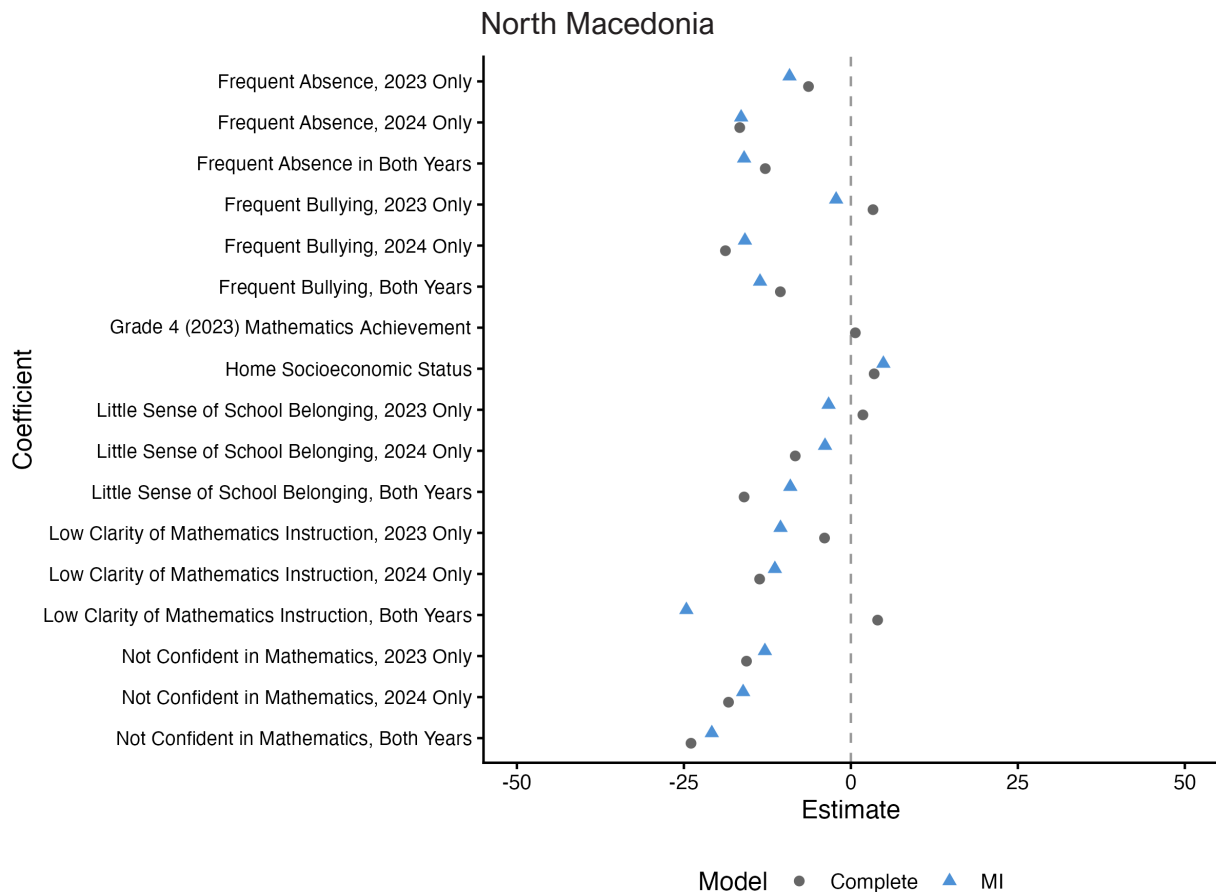
Exhibit C.10: HLM Estimates for Mathematics: Complete Cases versus Pooled MI Parameters (Continued)

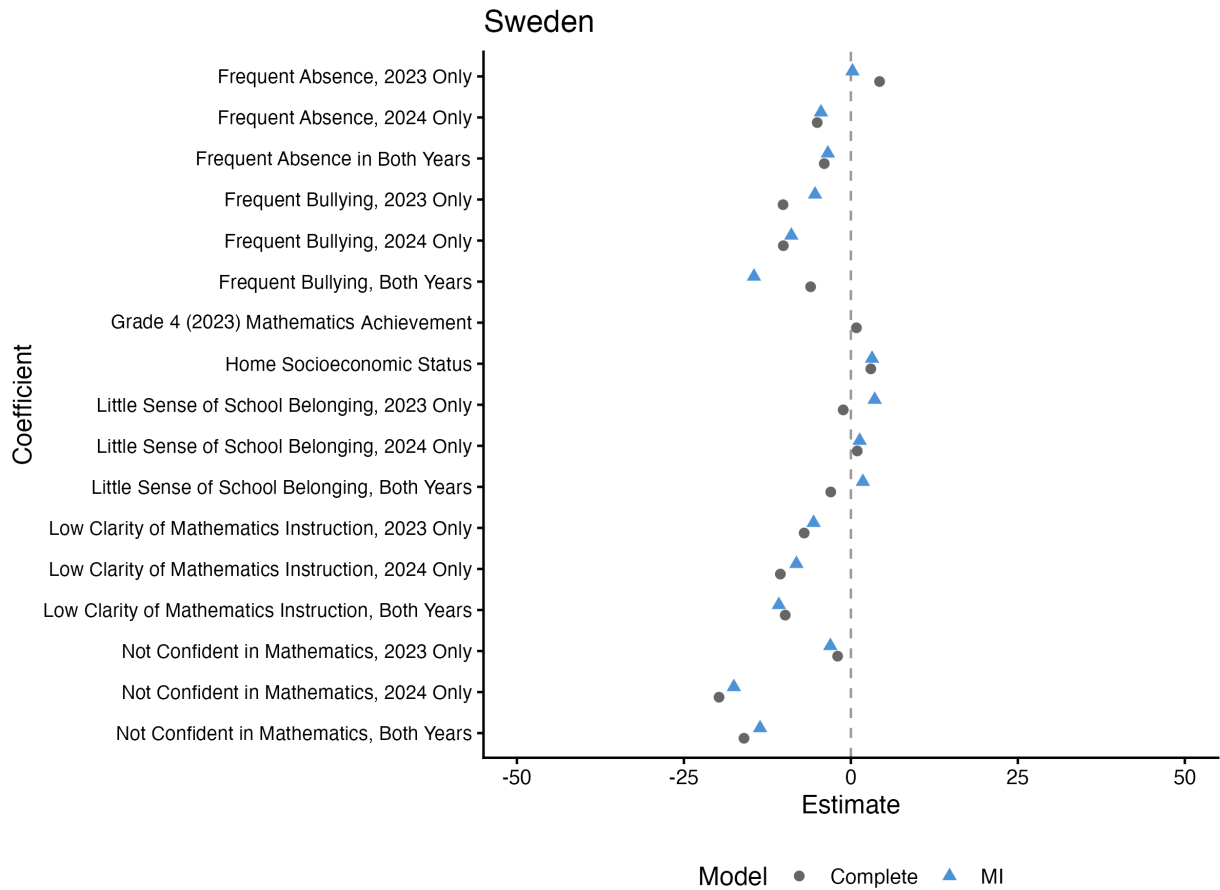
Exhibit C.10: HLM Estimates for Mathematics: Complete Cases versus Pooled MI Parameters (Continued)

Exhibit C.11: HLM Estimates for Science: Complete Cases versus Pooled MI Parameters

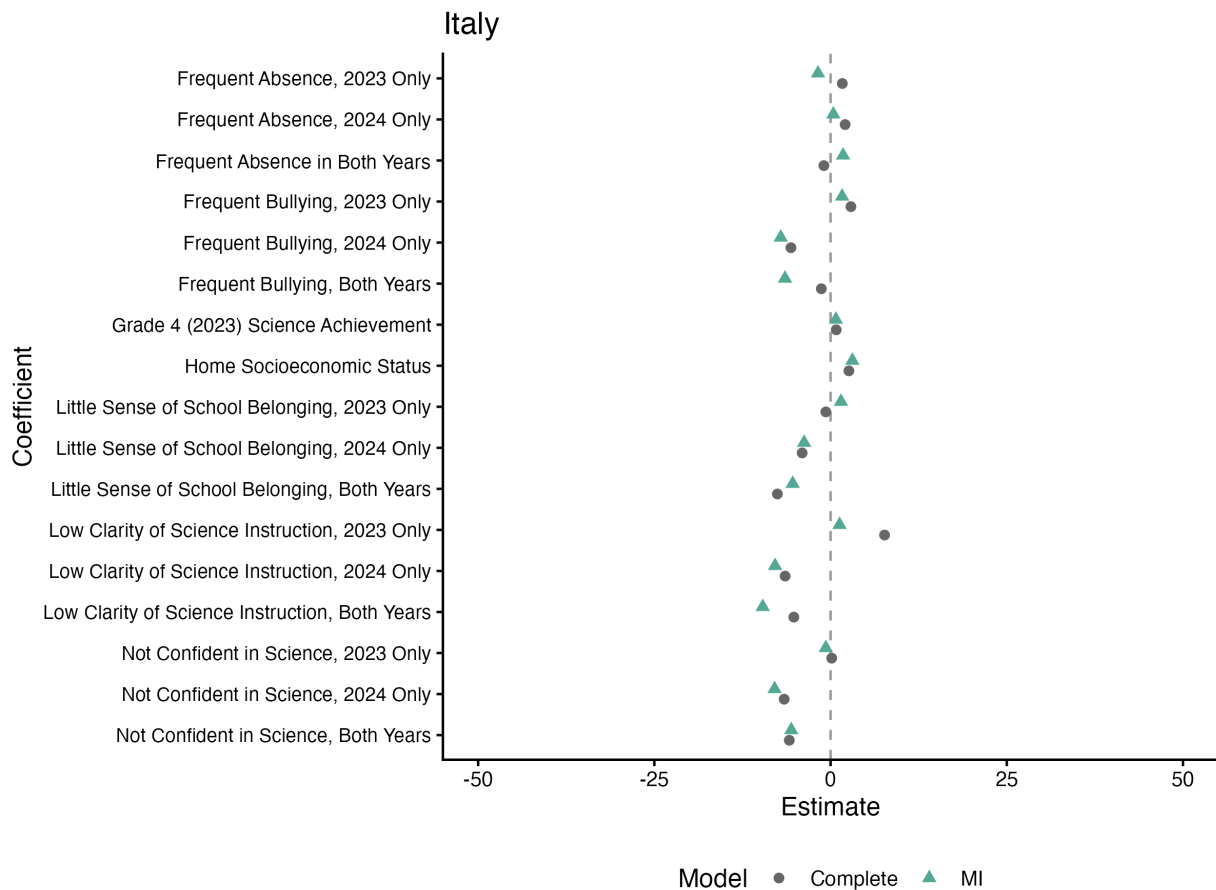
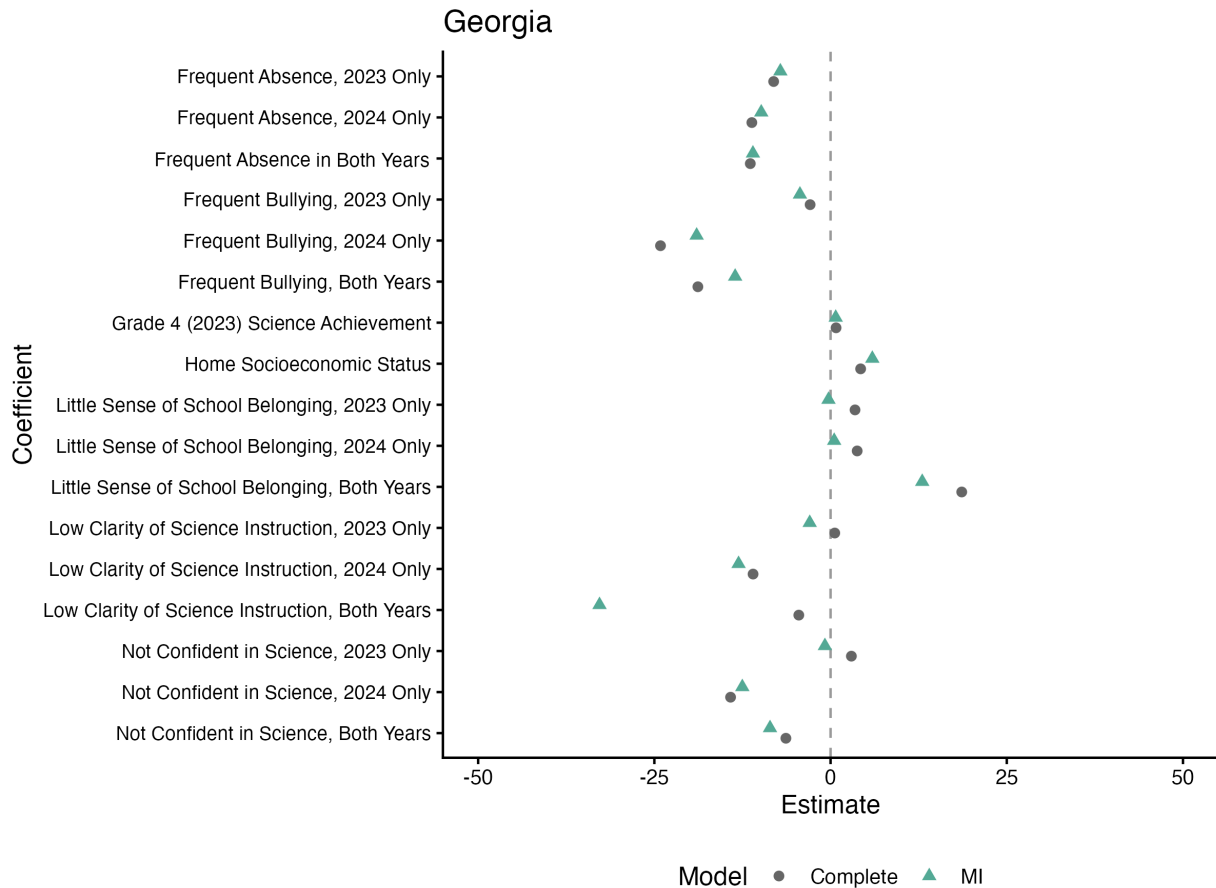


Exhibit C.11: HLM Estimates for Science: Complete Cases versus Pooled MI Parameters (Continued)

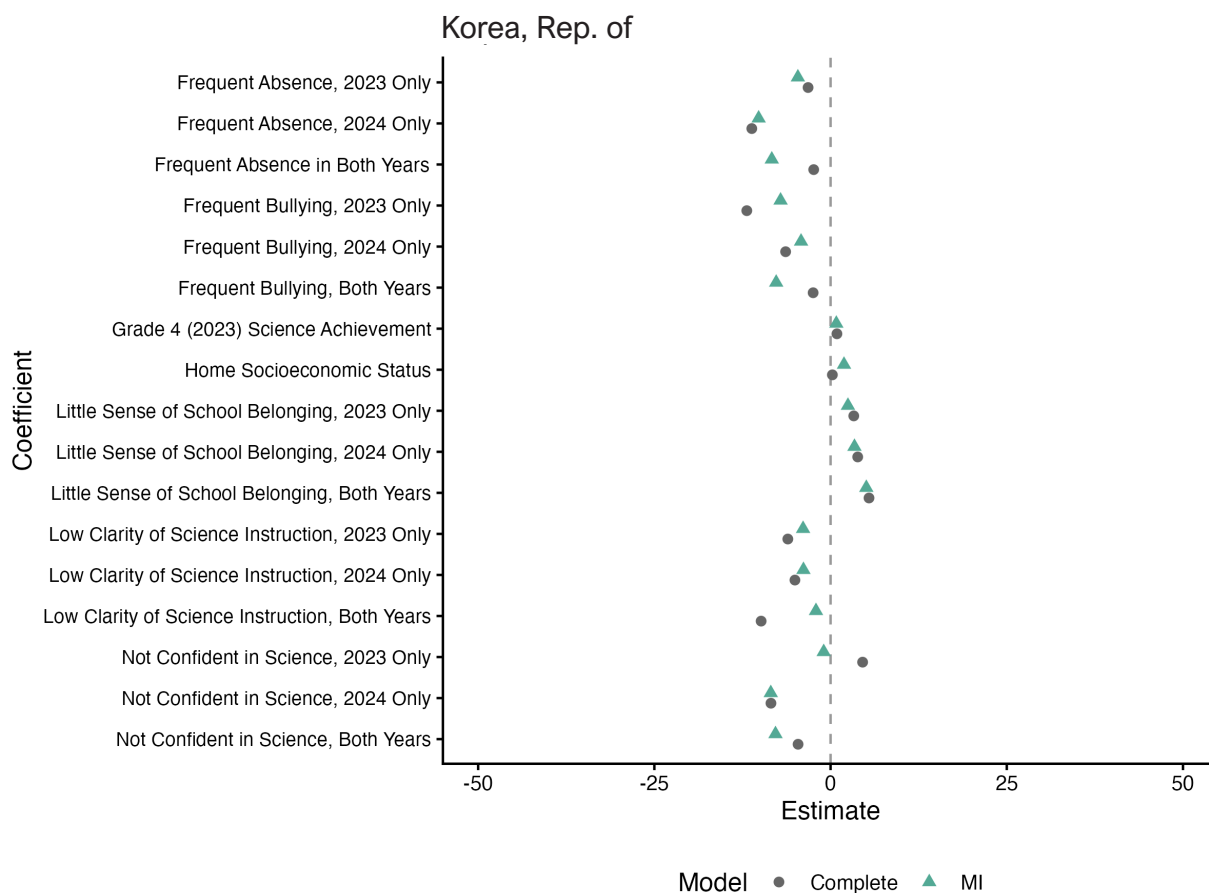
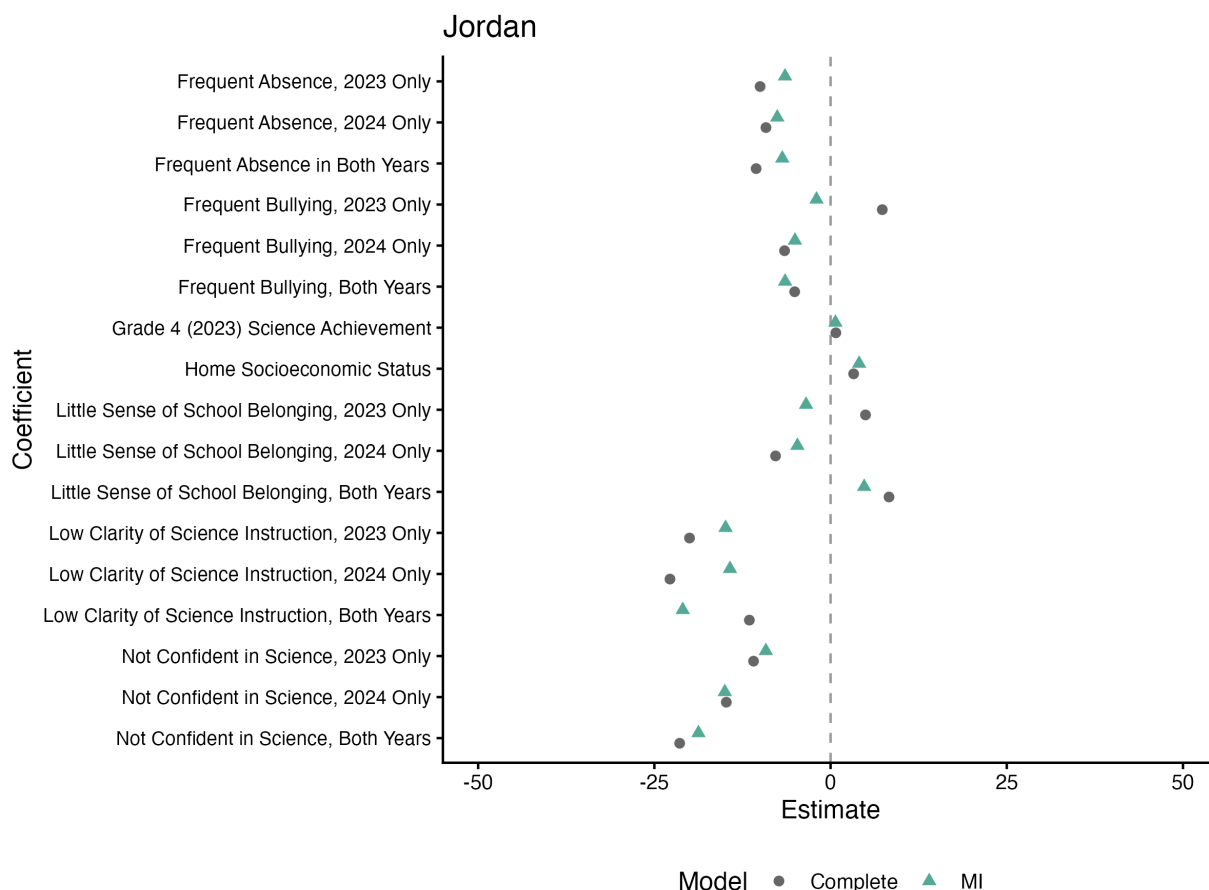


Exhibit C.11: HLM Estimates for Science: Complete Cases versus Pooled MI Parameters (Continued)

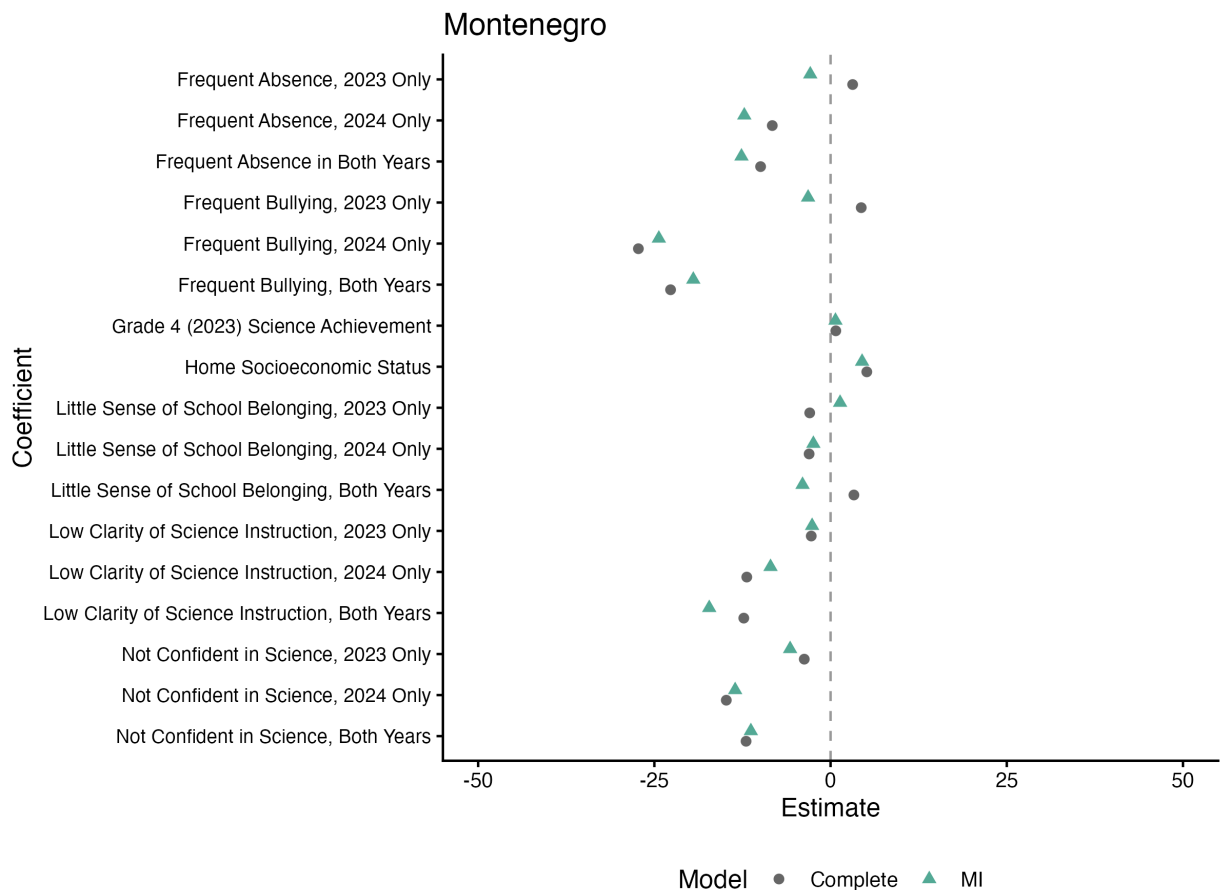
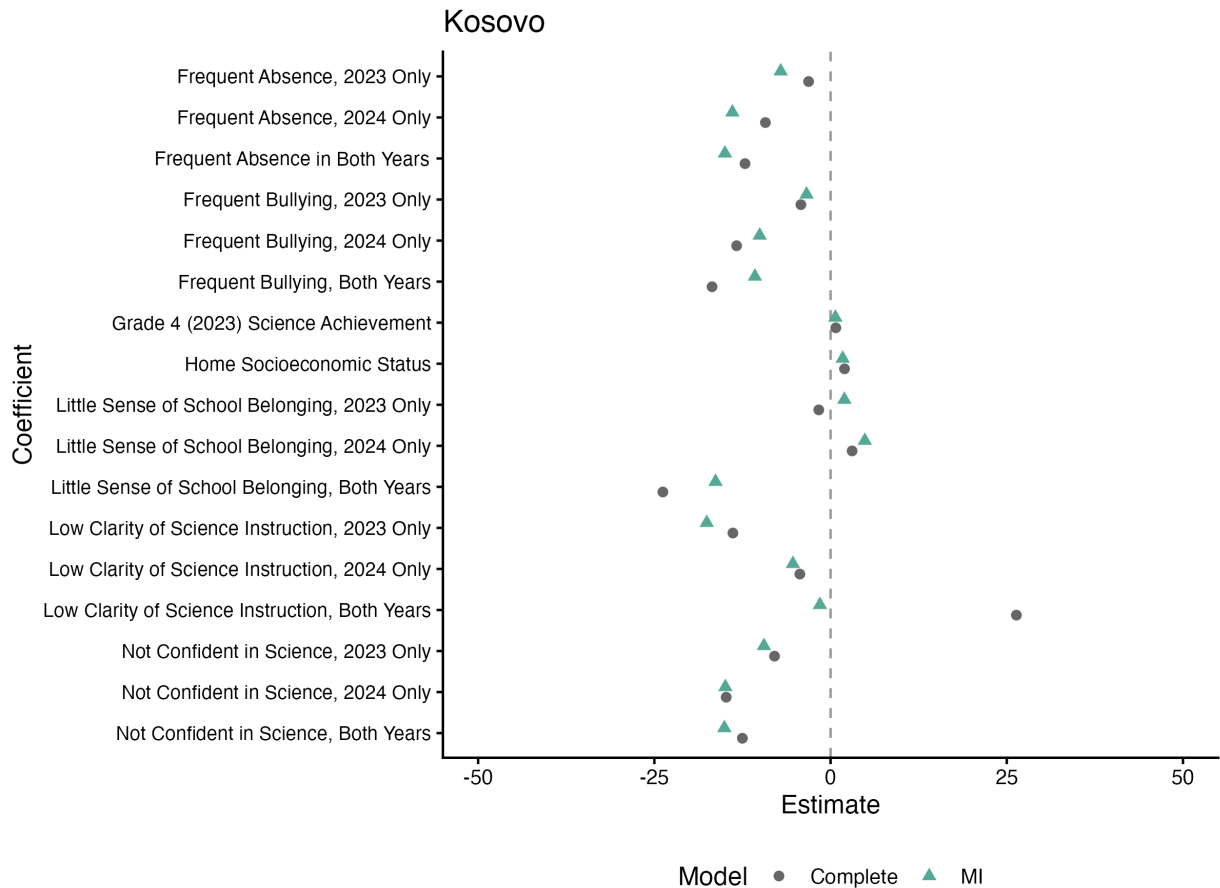


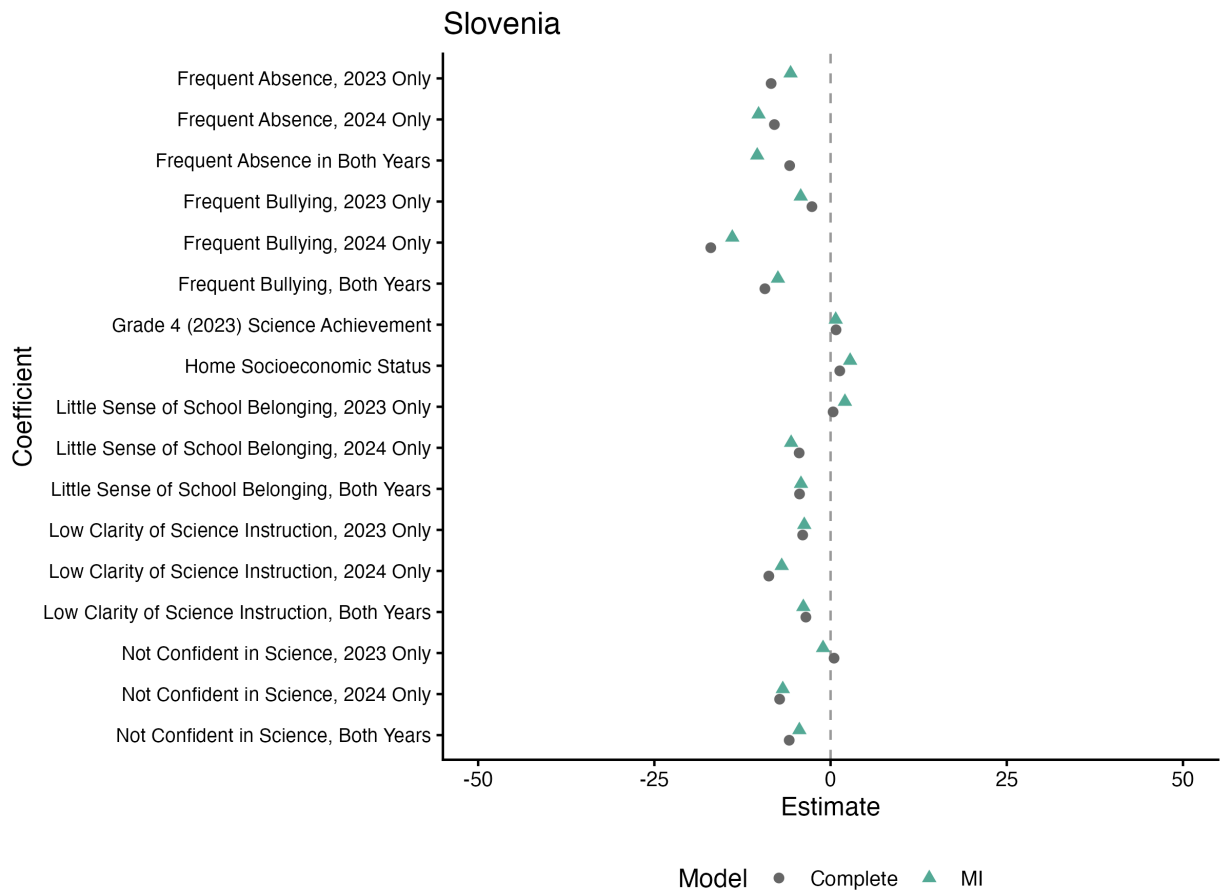
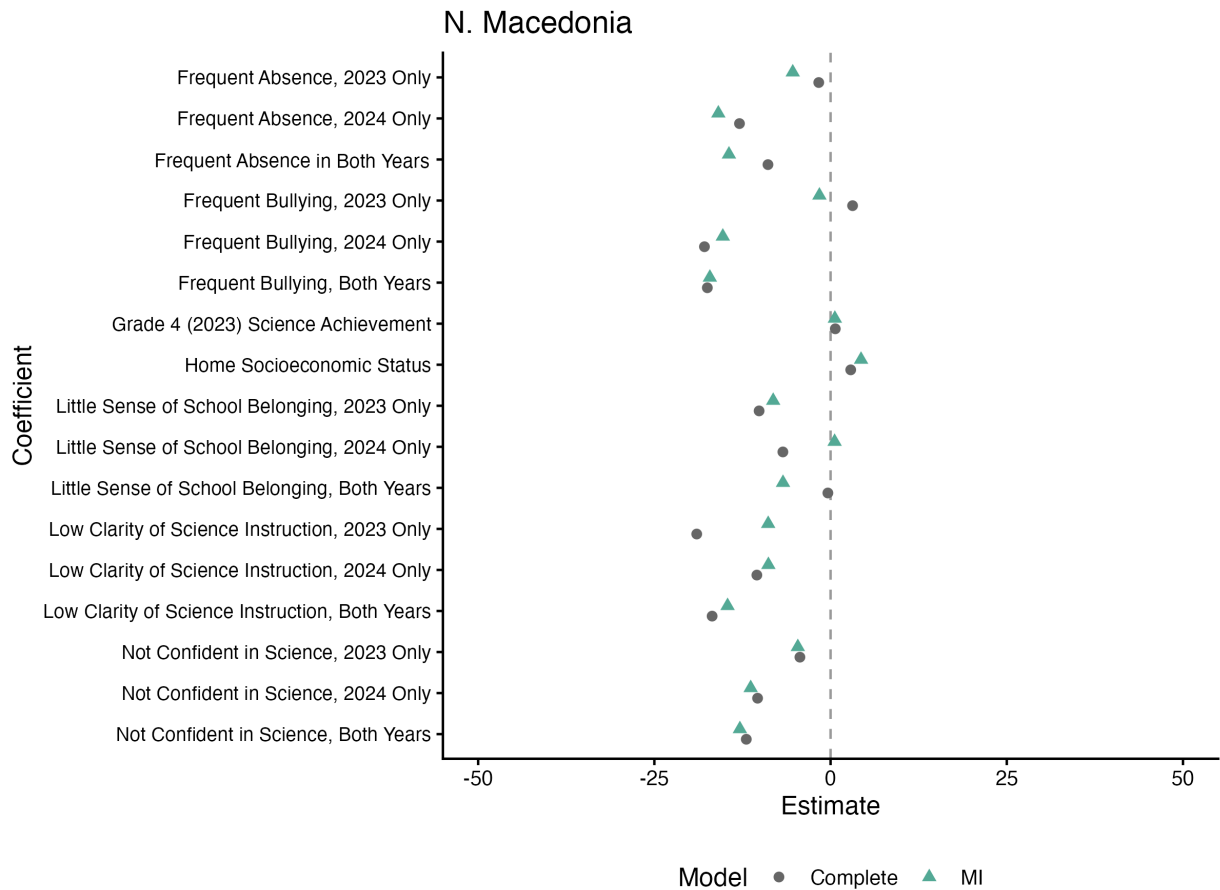
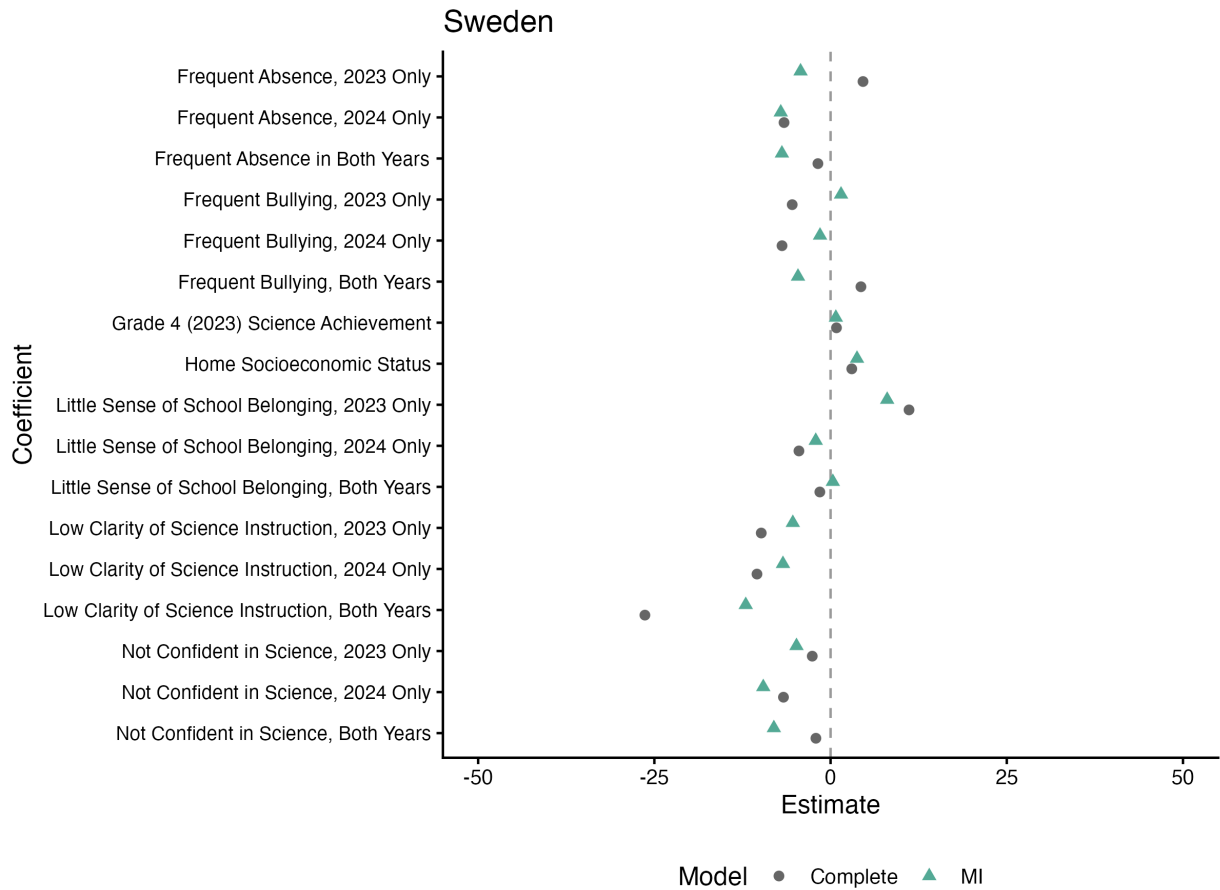
Exhibit C.11: HLM Estimates for Science: Complete Cases versus Pooled MI Parameters (Continued)

Exhibit C.11: HLM Estimates for Science: Complete Cases versus Pooled MI Parameters (Continued)



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