Indirect effects of bullying on school mathematics achievement in Chile

Abstract

Students who experience bullying at school present different negative outcomes, including lower academic achievement. However, the process by which bullying is connected to academic achievement is not clear. Using the Trends in International Mathematics and Science Study (TIMSS) dataset from Chilean schools in 2011, we sought to estimate the indirect effects of bullying on mathematics achievement via two key socio-motivational factors, namely school belonging and students' engagement. Results of our multilevel latent covariate analyses showed that schools' bullying rates were predictive of school differences in mathematics achievement, but that these effects were explained by broader characteristics of the school environment such as perceived levels of safety and discipline. Crucially, the hypothesized indirect pathway was evident at the within-school level, showing that individual experiences of bullying are related to a poorer sense of belonging with the school as a whole, as well as poorer classroom engagement.

Keywords: bullying, belonging, engagement, achievement, multilevel

Introduction

Violence tends to disproportionally affect youths (Vivolo et al., 2011). Elgar and colleagues (Elgar et al., 2009), using the Health Behavior in School-aged Children (HBSC) survey, estimated rates of self-reported bullying for 37 countries among 11 year old students. The rates vary between approximately 1.8% and 20% (Mean=9%, SD=.1%). Similarly, Contreras and colleagues (Contreras et al., 2015), using secondary data from Trends in International Mathematics and Science Study 2011 (TIMSS 2011), estimated the rates of experiencing being a victim of bullying among 52 countries. Researchers found, that among 4th graders, between 3.4% to 48.7% (Mean= 13.1%, SD=8.7%) have experienced at least one form of physical violence in the last month. Thus, victimization is considered a common experience in elementary and secondary school (Jansen et al., 2012).

Previous literature on school bullying in large scale assessment settings has focused on the size of the relationship between bullying and achievement (Engel et al., 2009; Ponzo, 2013; Román & Murillo, 2011). However, these studies do not answer why bullying is connected to academic achievement. Furthermore, although traditional multilevel models are informative of the effect of covariates at different inferential levels, there are plausible interrelations between the covariates in the model. Thus, these model specifications cannot account for complex relations such as indirect effects. To overcome these limitations in the present study, we fitted a theory driven model, estimated contextual effects with a multilevel model, and with a multilevel structural equation model we estimated the indirect effects of bullying on math achievement, via belonging and academic engagement.

The contextual route study allows to identify which school factors may account for the large differences between schools regarding the rates of bullying events. In contrast, the belonging-engagement link can tell us what the conceptual connection between bullying and academic outcomes is. Bullying is a stressful event that damages the motivation process of students, across schools.

Bullying and school adjustment

Experience of school bullying is known to have detrimental effects on pupils' wellbeing and school adjustment. Depression, anxiety and in worst cases suicide have been linked to experiences of bullying (e.g., Espelage & Holt, 2013; Hertz et al., 2013).

In addition, bullying has been reported to have a negative association with academic achievement. Meta-analytic estimates for the relation between bullying victimization and academic achievement suggest an *r* of -.10 (Nakamoto & Schwartz, 2010). Causal inference estimates, which compared bullied students and non-bullied students, matching students on a range of other characteristics, found differences of 9-13 points with TIMSS 2011 and PIRLS 2006 among the Italian students. These estimates are of similar effect size as class reduction or the improvement of teaching abilities (Ponzo, 2013). Perhaps partly related to these effects, bullying experience also has being associated with lifelong consequences, such as later violence, conviction, drug use and low job status (Farrington & Ttofi, 2011; Ttofi et al., 2012).

Bullying is a cause of concern, not only for victims of bullying, but also for schools, because bullied students may show counter-violence. In its most extreme form, bullying has been linked to school shootings in the US (Cunningham, 2007). In fact, the Secret Service assert one commonality among school shooters in the US: 71% of them had been targets of bullying (Espelage et al., 2013). Thus, in broad terms, bullying appears to feed more violence. However, who is the bully and who is the bullied can vary in time within schools (Taki, 2009). Thus, bullying is not only an individual experience; it also behaves as a group phenomenon.

Contextual effects of bullying

Bullying behaviour is a social group process highly present in the school environment (Azeredo et al., 2015; Woods & Wolke, 2004), and is understood to display contextual effects. For example, peer group level aggressive behaviour at time 1 moderate individual student aggressive behaviour at time 2, even after controlling for individual differences. Thus, students in more violent peer groups are more likely to display aggressive behaviour (Espelage et al., 2003). Classroom bullying levels also moderates the relationship between rejection and victimization for girls. Thus, in classrooms with higher rates of bullying, rejected girls are more likely to be victims of bullying, than in classrooms with lower levels of bullying (Isaacs et al., 2013). Indeed, schools with higher levels of bullying rates are expected to have students with lower wellbeing, even after controlling for students' own experience of bullying (Konu et al., 2002). These negative links suggest that schools with higher levels of bullying most likely offer inferior environments for learning.

In fact, the contextual effects of differences in the prevalence of bullying are likely to extend to academic outcomes. Schools with higher bullying rates have been associated with higher dropout rates (e.g., Cornell et al., 2013; Townsend et al., 2008), and school-level regressions with data from Virginia in the US have found negative relations between school prevalence of bullying and school passing rates on an academic achievement test (Lacey & Cornell, 2013). Multilevel estimates of bullying rates reported by school principals in Canada are consistent with the same picture: schools with higher bullying rates yield lower academic results (Konishi et al., 2010). Engel and colleagues (Engel et al., 2009) using secondary data from TIMSS 2007, also found a negative relation between school level bullying and academic achievement across different countries (27 out 49) from Europe (e.g., Hungary, Ukraine), Asia (e.g., Singapore, Hong Kong) and the Middle East (e.g., Israel, Jordan, Lebanon). Román & Murillo (2011), using secondary data from the Second Regional Comparative and Explanatory Study (SERCE), estimate the relation between the experience of bullying and classroom bullying rates across 15 Latin-American countries. The authors found consistent contextual effects of bullying rates across countries. That is, classroom-bullying rates have a consistent negative relation with academic achievement, regardless of students' individual experience of bullying.

Conceptual Model

Buhs and colleagues (Buhs et al., 2006, 2009) propose an indirect effect model for the link between peer rejection and achievement. In this model, the authors stipulate that academic achievement is damaged by peer rejection because of two reasons: students who suffer from peer rejection tend to participate less in classroom activities because of their social exclusion; and students who suffer peer maltreatment will avoid school as a whole. The general model can be expressed by the following sequence: peer rejection leads to chronic peer victimization, and to lower classroom participation, which in turn, leads to achievement problems. In this framework, bullying is an example of student victimization. One of the main assumption of this model is that aversive social experiences are stressful for people, who proceed to exhibit social and emotional disengagement from the source of stress (Buhs et al., 2009). Although the original model of Buhs and colleagues has been tested with young school children (pre-primary and primary students) studies with 9th graders support the first path: from bullying to engagement (Mehta et al., 2013). Thus, bullying is expected to have negative effects on students' school involvement, because of its aversive effects and students' consequent engagement.

Research on engagement and academic achievement (Lee, 2014) asserts that emotional engagement with the school (feelings of school belonging) influences academic achievement indirectly, via behavioural engagement. Lee (2014) supported the engagement hypothesis using secondary data from the Program for International Student Assessment 2000 using the US sample. The implication of this model is twofold: a) more emotionally engaged students are more likely to put greater effort into classroom activities, and thus achieve better results; and conversely b) more emotionally disengaged students are less likely to put higher effort into classroom activities, and thus achieve worse results.

Additionally, the work of Konishi and colleagues (Konishi et al., 2010) suggests that school connectedness may also act as a *buffer* against the negative effects of bullying. School connectedness, school belonging, and school bonding are all different forms of emotional engagement with the school environment (Wormington et al., 2016). The buffer hypothesis states, in positive terms, that even if students suffer from bullying they may get average achievement results to the extent that teachers and peers sustain their sense of school belonging (Norwalk et al., 2015). Moreover, the negative implication of the buffer hypothesis, entails that if students already feel disengaged from the school environment, and suffer from bullying, more negative results are expected, in contrast to students with average levels of school emotional engagement.

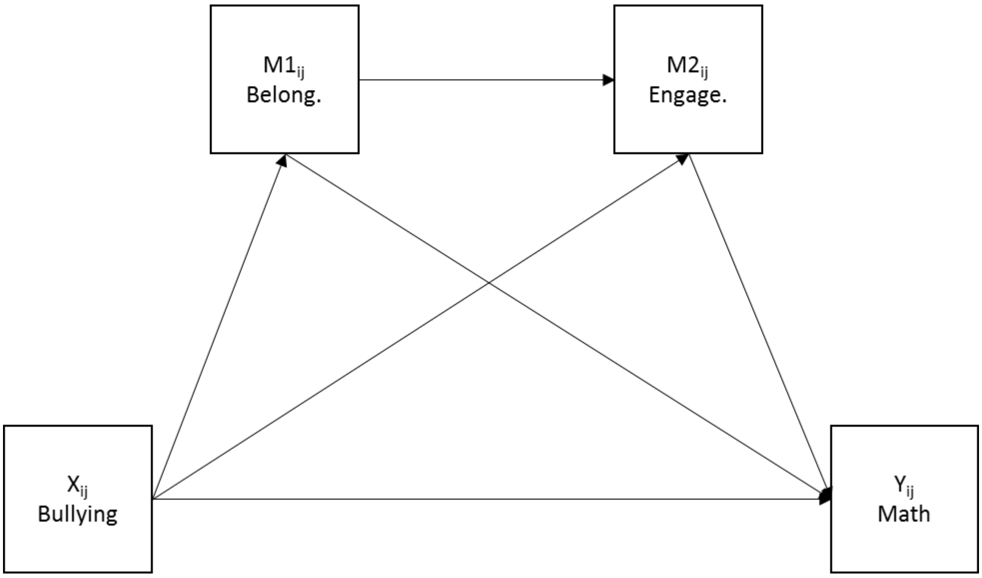
The Present Study

Chile is a country with a notably high prevalence of bullying. The Global School-Based Health Survey 2004, which surveyed students at ages 13 to 15 years, shows that 47% of Chilean students have been bullied in the past month, at the moment of the survey (Fleming & Jacobsen, 2009). The "Encuesta Nacional de Juventud" from 2012, estimates that about 29% of youth (covering ages 15-29 years) have experience some form of physical or psychological form of violence at school (INJUV, 2013). Chile appears in 6^{th} place for physical violence victimization among 4^{th} grade students in TIMSS 2011, with a rate of 18.4% (Contreras et al., 2015). As such, this is a topic of great concern.

The mentioned views of engagement and its expected effect on student withdrawal behaviour because of bullying are complementary. We integrate these previous models under the causal assumption that bullying has negative effects on academic achievement because it negatively affects the engagement process of students with learning. We can express the expected general relations in the following manner: being bullied leads to lower school belonging, leading to lower classroom engagement, finally leading to lower achievement (see Figure 1). It is not yet clear if the same mechanism can explain variations in achievement within and between schools but given the previous literature on school-level associations between bullying prevalence and academic achievement, we expect between-school effects different from within-school relations. In other words, schools with higher levels of bullying are expected to have students with lower levels of school belonging and classroom engagement, and thus present lower academic results. Additionally, to operationalize the buffer hypothesis of school belonging, we include an interaction term between bullying and students sense of belonging. Finally, we include socio demographics (age, sex), and school broader characteristics (e.g., school SES intake, type of school administration and school principal rates of safety, discipline, and academic emphasis) as control variables which have known effects on school achievement (Mullis et al., 2012).

To summarise, in the present study, our line of inquiry is twofold. We are interested in the contextual effects of bullying on school outcomes, as well as the motivational route by which bullying is indirectly linked to academic achievement. Our research questions are: a) To what extent school-level variation in academic achievement can be explained by school-level variation in bullying?, and if so, is this the case over and above broader school characteristics such as overall levels of discipline, safety and academic emphasis? and b) Are individual, within-school experiences of bullying predictive of academic achievement, and if so, are these explained by feelings of school belonging and engagement?

Figure 1 Conceptual model



Method

Participants and Data sources

We use the national representative sample of eighth graders from Chile in the Trends in International Mathematics and Science Study 2011 (TIMSS 2011). The Chilean data comprise a nominal sample of 5835 students, nested in 193 schools, with a mean age of 14.20 and a balanced gender population (Female=53.01%, SE=.01). This study uses a two stage sample probability design, in which schools are randomly sampled, and intact classrooms are selected at a second stage from the target 8th grade (Joncas & Foy, 2011).

Measures

Math attainment. TIMSS 2011 used a matrix sampling design in which students answered one of fourteen randomly assigned booklets, comprising of 24 to 36 math items (Mullis et al., 2009). These items covered different mathematics domains such as numbers, algebra, geometry, and data and chance competency. Furthermore, these questions were designed to measure knowledge, application, and reasoning. Students' responses were modelled via item response theory (IRT), and 5 plausible values are generated to represent population proficiency levels (Von Davier et al., 2009). These scores were set to have a mean of 500 and standard deviation of 100 for all participating countries. All analyses in the current manuscript, including this outcome were conducted including all five plausible values, using imputation techniques to yield combined estimates (Rutkowski et al., 2010).

Socioeconomic status was measured by combining students' responses to "Number of Books at home", "Number of study supports" (internet connection, own room, both)", and highest level of education of either parent. These questions were modelled via partial credit IRT, set to a mean of 10 and SD of 2 (Martin et al., 2011), whereby a higher number means a higher socio economic status. In the present study, we used the provided estimates from the TIMSS 2011 data release.

School administration. Three dummy variables were created to identify private school, public schools and subsidized schools. This information was retrieved from the stratification variables from the public data release. We set public schools as the reference category.

Gender. This was dummy coded, leaving males as the reference category (female=1, male=0).

Age. Students' age was computed in years, using the test date as a reference. We divided this covariate into three groups: Younger, Expected and Older. We categorized all students according to their implied age of entry at year one of primary school, by March 31 2003. Thus, students who were younger than 6 years at that point were classified as younger, those students who were between 6 to 7 were classified as the expected age, and those students who were aged 7 years or more were categorized as older. This last group may correspond to students who may have suffered from previous grade retention.

Engagement. Students indicated their level of agreement, using a Likert type scale of 4 levels, to five different items, such as: "I am interested in what my teacher says", "My teacher gives me interesting things to do", "I think of things not related to the lesson" (reverse coded). These responses were modelled using a partial credit IRT, and were set to an international mean of 10 and standard deviation of 2 (Martin et al., 2011), where higher scores meant more student engagement. We used the IRT scores present in TIMSS 2011 released data.

Belonging. Students indicated how much they felt a part of the school, expressing their levels of agreement to three items: "I like being at school", "I feel safe when I am at school", "I feel like I belong at this school", using a four level Likert type scale. We created a score with the responses to each of these items, by averaging its response values, were higher values means students express a higher sense of belonging. This created score yields an observed alpha of .69.

Bullying. Students indicated the frequency with which they experienced different forms of bullying at school, such as: being called names, being left out, being physically hurt, being forced to do things by other students. In total, this scale included 6 items, to each of which students responded if the event has ever happened, happened a few times a year, once or twice in a month, or at least once week. A scale score was generated, using a partial credit IRT model, scaling its international mean to 10, and its standard deviation to 2, where higher scores meant less experience of bullying by students. This score was discretized into three ordinal levels of frequency of bullying, at weekly, monthly, and almost never bullied in the public data file (Martin et al., 2011). Both scores are present in TIMSS 2011 released data. We used this latter indicator, and generated a dummy variable used throughout the present study. Those students who suffered from some form of bullying, weekly or monthly were coded as 1, and the remainder of the students were left as the reference category.

School safety. Math teachers from the target grade from each school indicated their level of agreement to five different items referring to school safety and order. This scale included items such as: “This school is located in a safe neighbourhood”, “I feel safe at school”, “The students are respectful of the teachers”. Teachers’ responses were modelled via a partial credit IRT, like the rest of the scales, such that higher numbers in the scale indicated relative safer schools. This covariate is fixed between schools as only one math teacher per school answered this question.

School discipline. School principals’ responses to 11 items were combined using a partial credit IRT model, and set to M=10, SD=2 for the international average (Martin et al., 2011). This scale assessed the extent to which various student behaviours were problematic within the school, including items such as: arriving late at school, vandalism, theft, intimidation and physical violence. Higher values in this scale indicate higher school discipline.

Academic emphasis. School principals’ responses to 5 items were combined via partial credit IRT model with M=10, SD=2 for the international average of participating countries (Martin et al., 2011). This scale assessed the school emphasis on academic success. Exemplary items of this scale are: “Teachers’ expectations for student achievement”, “Parental support for student achievement”, “Students’ desire to do well in school”. Higher values in this scale indicate higher academic emphasis at the school level.

Analysis Strategy

TIMSS 2011 uses a complex sample design (Heeringa et al., 2009), in which schools are randomly selected, and in a second stage, intact classroom are selected, with an unequal probability. It is a requirement to account for its sampling design, to produce population estimates. Furthermore, this study uses the plausible values method (Von Davier et al., 2009), which combine estimates via imputation procedures, across all available plausible values (Rutkowski et al., 2010). We use appropriate variance estimations via fixed and/or mixed effects methods, to account for plausible values and sampling design (Stapleton, 2013; Sterba, 2009).

We first estimated the means, standard deviations and standard errors for our selected variables, as well as the effect size, expressed as *r* coefficient, for the relation between each covariate and Math attainment (see Table 1). We use a jackknife variance estimation to get valid population estimates via the PV module (Macdonald, 2014), and the SVR module (Winter, 2008) in STATA (StataCorp, 2013) in order to estimate these parameters. This procedure replicates official release results for the Chilean sample (Agencia de Calidad de la Educación, 2011). Additionally, to assess plausible sources of multi-collinearity among the selected covariates, we estimated the variance inflation factor for all variables. All covariates yielded a VIF<10, which is the threshold for concern (O’Brien, 2007).

To estimate the relative contribution of each factor onto math attainment, we fit a series of multilevel models using MPLUS v7 (Muthén & Muthén, 2017) to account for sampling design and plausible values, while scaling weights to effective sample size (Asparouhov, 2006; Rabe-Hesketh & Skrondal, 2006; Snijders & Bosker, 2012). This scaling weight method was preferred over other weight normalization methods, because it produces unbiased estimates of variances (Stapleton, 2002). These results are presented in Table 2.

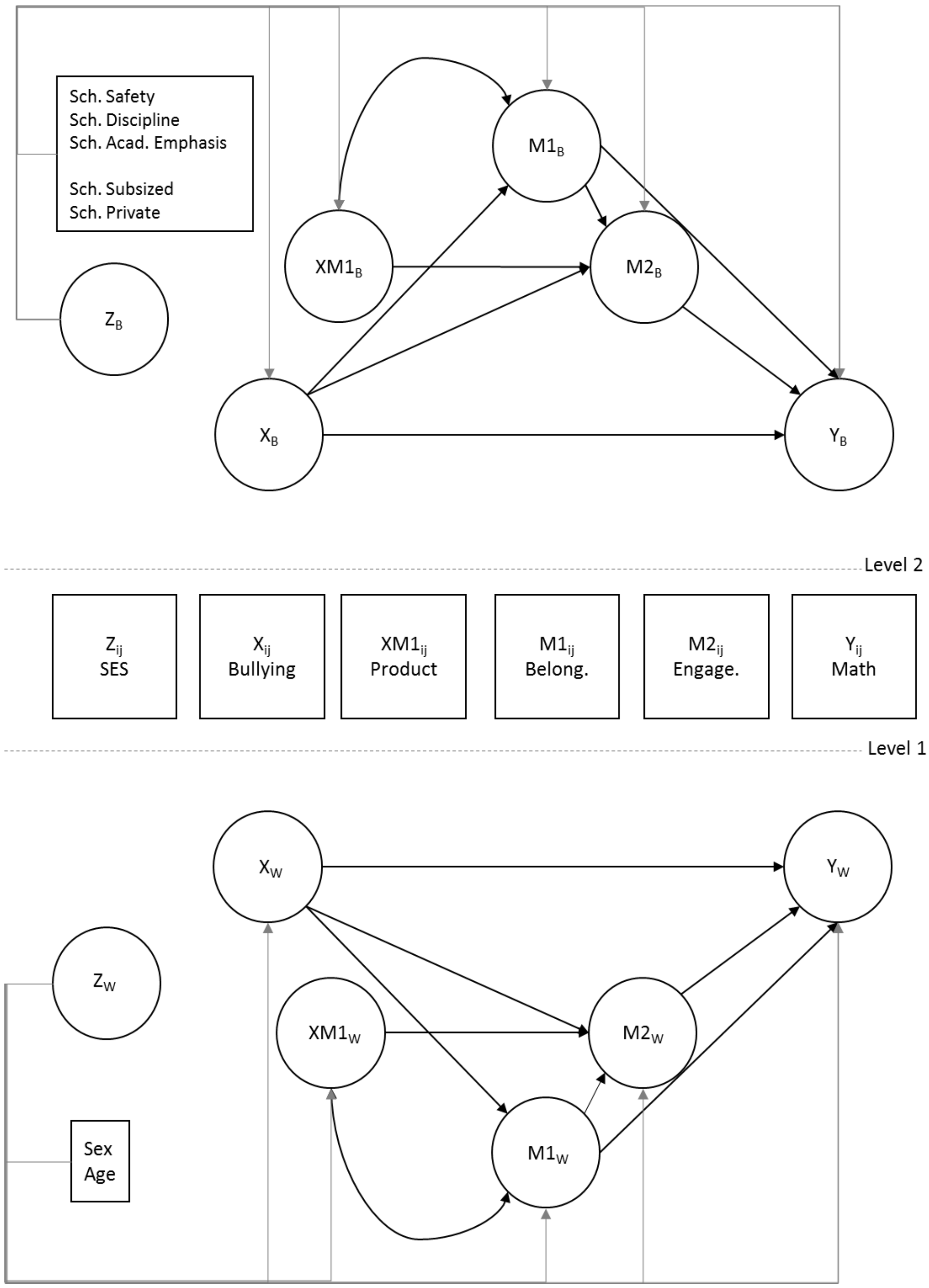
Underlying to the relative contribution of all factors to math attainment, there are several interrelationships. To properly estimate the indirect effects and moderation of indirect effects, we fit a multilevel structural equation model (Preacher et al., 2011b). Within this model, we fit a multilevel mediation with fixed slopes, which resemble the generic model I in Preacher, Zhang, and Zyphur (2011a). Additionally, we included a moderated mediation, in which the indirect effect is moderated by levels of a mediator (type Model 1, in Preacher, Rucker, & Hayes, 2007). In this model, we multiplied the bullying and belonging variables, centred to the grand mean, to get the best estimates of the moderation at the between level (Ryu, 2015). We again used MPLUS v7 to fit this model, including the sampling the design as before. We used this third approach to estimate the indirect effects of bullying onto math achievement, via belonging and engagement, jointly at within and between parts of the model.

As noted earlier, the relationship between the experience of bullying and academic achievement, is expected to be mediated by socio-motivational processes. We expected indirect effects on achievement, via the emotive side of motivation (belonging) and its attitudinal aspect in the school setting (engagement in math lessons). Additionally, we tested if belonging serves as a buffer for the negative effects of bullying on achievement. To assess if the indirect effects vary at different levels of the moderator, we calculated a Linear Moderated Mediation Index, LMM for short (Hayes, 2015), at each level.

We relied on a multilevel latent covariate model (Lüdtke et al., 2008), which enabled us to test if these indirect effects are present within or between schools, or both, after the inclusion of relevant covariates. The fitted model is presented in Figure 2; we follow Ryu's (2015) style of diagram, and depict latent variables as circles, at each level of the model, and use squares for manifest variables.

In the present study, we used the term "effect" as is customary in the literature of structural equation model, path analysis and mediation models. However we don't mean our results are estimates of causal inference, in the same sense as previous research we cite (e.g., Ponzo, 2013). We use the term effect, to refer to changes in conditional expectations (Rabe-Hesketh & Skrondal, 2012), present in our specified models. Although, the fitted models do follow a conceptually driven structure of relations between variables, and produce estimates generalizable to the population of students and schools (Sterba, 2009), these are not intended to equate causal inference estimates.

Figure 2 Multilevel SEM diagram



Results

Descriptives

Chile obtained a mean of 416 (SE=2.59) in Math attainment for the population of 8th graders, reaching the 31st position of 42 participating countries. The zero order correlation between students' socioeconomic status and attainment results in an *r* of .4, which is quite high in comparison to other countries in similar studies (Sirin, 2005). Similar effect sizes can be seen for other school factors, such as school administration (public r=-.34), school safety (r=.32) and academic emphasis (r=.34) when no other factors are considered. These results clarify the large differences between schools as educational environments in the Chilean case.

Table 1 Population descriptive estimates

	M	SD	SE	VIF	r
Outcome					
Math attainment	416.27	79.65	2.59	1.60	
Socio Demographics					
Socioeconomic Status	9.71	1.64	.05	1.38	.40
Gender					
Female[d]	.53	.50	.01	1.07	-.09
Male[d]	.47	.50	.01	----	.09
Age	14.21	.63	.01		.05
Younger[d]	.13	.34	.01	1.04	.01
Expected[d]	.71	.45	.01	----	.20
Older[d]	.16	.37	.01	1.14	-.26
Students Factors					
Engagement	9.86	1.77	.05	1.16	.11
Belonging	3.38	.64	.02	1.18	.10
Bullied					
Almost never[d]	.62	.49	.01	----	.10
At least monthly[d]	.38	.49	.01	1.07	-.10
School Factors					
School Administration					
Public[d]	.46	.50	.01	----	-.34
Subsidized[d]	.47	.50	.01	1.36	.15
Private[d]	.07	.26	.00	1.59	.36
School Safety	9.44	2.35	.18	1.36	.32
School Discipline	9.65	1.78	.15	1.61	.26
Academic Emphasis	8.74	2.37	.17	1.68	.34

Note: covariates flagged with [d] are dummy variables, hence their mean estimates are equivalent to percentages estimates. M=Mean, SD= Standard Deviation, SE=standard error, VIF=variance inflation factor, r=Pearson correlation, "----" are reference categories for dummy variables. Variance Inflation Factor was estimated using only the first plausible value.

Multilevel estimates

Model sequence. The full model sequence in Table 2 shows the relative contribution of each factor to explain math achievement. The null model, presents an intra class correlation of .43 (see Table 3), indicating that a large amount of the variance of Math achievement is located between schools. Socioeconomic status of the students, the school mean of socioeconomic status, and the type of schools' students are attending (Public, Subsidized, Private) accounts for 1% and 61% for the variation of Math achievement, at the within and between levels, respectively (see M1 in Table 3). The socio-demographic factors of sex and age of students were included as controls and accounted for 8% of additional within variance, and 13% of additional between variance (M2). The contribution of students' experience of bullying, belonging and engagement, altogether accounted for 2% and 19% of additional variance in achievement within and between schools respectively, after the effects of socioeconomic status, sex and age of students have been controlled for (M3 vs M5). Finally, the inclusion of the school fixed factors of school safety, school discipline, and school academic emphasis account for an additional 20% of between variance (M6). Overall, the full model accounts 12% for students' variance and 81% of the variance between schools. Each block of variables included in the model sequence improved the model fit at each step (see the LRT results in Table 3, comparing each model with the previous model in the sequence).

Main effects (M6). Students' SES was positively related to academic achievement. For every 1 point more above the mean of SES within schools, students were expected to score 4.55 points (SE=.94, p<.01) higher on math achievement in contrast to their schoolmates. Similarly, schools with 1 more point above the SES mean presented 23.46 points (SE=4.27, p<.01) above the estimated grand mean for achievement. The contextual effect of this factor is therefore estimated at 18.91 points (SE=4.29, p<.01). Thus, the expected difference in math achievement between two students with similar SES characteristics, who attend schools differing by 1 unit on the school SES mean, would differ on 18.91 points in mathematics achievement, which is .24 standard deviations of the outcome. Additionally, private schools achieve 44.33 points (SE=13.13, p<.001) more over the grand mean of schools, even when all other factors are controlled for.

Socio-demographics factors were of great relevance. Female students were expected to achieve 22.39 points (SE=2.80, p<.01) less than their male counterparts, while in terms of age, only the ‘older’ students differed from the rest, scoring about 38.36 points lower (SE=3.35, p<.01) than the students with the ‘expected’ age. Because these factors were entered as controlled variables, these are centred to the grand mean. Thus, all effects are estimated regardless of school composition in terms of sex and age (Heck & Thomas, 2015).

In model 5, bullying, belonging and students’ engagement presented interesting effects, before we controlled for other school factors. In this model, bullying and belonging showed larger effects between schools, than within schools. Thus, this entails significant contextual effects: students who attended schools where 100% of the students reported bullying could be expected to achieve 48.55 points lower (SE=19.28, p<.05) than schools at the grand mean of bullying. If we change the metric of the covariate to increments of 10%, it means that for every 10% increase in the bullying rate at the school level, schools may be expected to achieve 4.85 points lower than the average schools. With respect to school belonging, students who attended schools with 1 point over the grand mean of school belonging would be expected to achieve 43.75 points (SE=11.55, p<.01) more on mathematics. If students’ characteristics are held constant, these are the expected differences attributable to the school environments. In contrast, students’ classroom engagement did not present larger between effects over within effects. More engaged students present higher scores in math achievement in comparison with their peers (b=5.88, SE=.90, p<.01, see M5 in Table 2).

However, when school safety, school discipline and school academic emphasis were controlled for, these contextual effects no longer reached statistical significance (see M6 in Table 2). For each unit of change of School Academic Emphasis, schools reach 3.97 points over the grand mean (SE=1.25, p<.01). Similarly, schools higher in School Safety could be expected to have 2,77 points more, for every unit of change (SE=1.27, p=.03), although differences in school discipline did not explain much variance in achievement (b=.79, SE=1.56, p=.62). In the final model, bullying, belonging and engagement did not present significant relations between schools because the previously observed estimates seems to be accounted by schools’ levels of safety and academic emphasis. At the within level, however, differences between students’ engagement within schools do present a relation with math achievement. For 1 unit of change in engagement, students achieved 6.01 points more (SE=.89, p<.01) than their schoolmates.

Table 2 Multilevel fixed effects estimates explaining Math Attainment

		M0		M1		M2		M3		M4		M5		M6	
	Intercept	405.52	***	410.51	***	411.23	***	412.33	***	412.51	***	412.05	***	412.00	***
Between School Factors															
	School mean SES			27.18	***	24.95	***	23.11	***	26.10	***	26.85	***	23.46	***
School	Public (reference)														
Administration	Subsidized			12.88		14.13	*	12.54		12.23	*	12.80	*	7.19	
	Private			49.40	**	56.06	**	48.92	**	44.48	**	45.52	***	44.33	**
School Factors	Bullying							-68.86	**	-48.94	*	-48.95	*	-34.18	
	Belonging									50.72	***	42.40	***	23.15	
	Engagement											6.96		7.42	
	School Safety													2.77	*
	School Discipline													0.78	
	Academic Emphasis													3.97	**
Within School Factors															
SES	Student SES			5.49	***	4.34	***	4.33	***	4.33	***	4.05	***	4.55	***
Demographics	Sex														
	Female					-23.41	***	-23.75	***	-24.31	***	-22.96	***	-22.39	***
	Male														
	Age														
	Younger					0.80		0.84		0.80		0.14		-0.41	
	Normal														
	Older					-38.91	***	-38.35	***	-37.48	***	-36.88	***	-38.36	***
School Experience	Bullying							-2.00		-1.35		-0.40		-0.56	
	Belonging									3.67		-1.35		-0.36	
	Engagement											5.88	***	6.01	***
Contextual effects															
	SES			21.69	**	20.61	**	18.78	**	21.77	***	22.80	***	18.91	***
	Bullying							-66.87	**	-47.59	*	-48.55	*	-33.62	
	Belonging									47.05	**	43.75	***	23.51	
	Engagement											1.09		1.40	

Note * $p<.05$; ** $p<.01$; *** $p<.001$.

Table 3 Multilevel random effects and fit indices

	M0		M1		M2		M3		M4		M5		M6	
Variances														
Within	3659.73	***	3611.8	***	3327.53	***	3325.48	***	3320.69	***	3239.57	***	3207.00	***
Between	2785.63	***	1071.51	***	929.49	***	815.59	***	679.28	***	668.79	***	533.45	***
ICC	0.43	***	0.23	***	0.22	***	0.2	***	0.17	***	0.17	***	0.14	***
Model Fit														
Deviance (-2LL)														
-2LL (mean)	65093.92		64531.99		64045.41		63546.03		63493.45		63057.17		53359.61	
(SD)	120.45		135.73		150.17		143.26		145.64		126.91		98.77	
Parameters	3		7		10		12		14		16		19	
LRT (p value)			0		0		0		0		0		0	
Pseudo R^2 (M_0 vs M_k)														
R^2 Within			0.01		0.09		0.09		0.09		0.11		0.12	
R^2 Between			0.62		0.67		0.71		0.76		0.76		0.81	
Pseudo R^2 (M_k vs M_{k+1})														
R^2 Within			0.01		0.08		0.00		0.00		0.02		0.01	
R^2 Between			0.62		0.13		0.12		0.17		0.02		0.20	

Note * p<.05; ** p<.01; *** p<.001.

Multilevel Latent Covariate Estimates/Multilevel SEM

Overall fit. Because MPLUS estimates one model for each of the plausible values, each fit index has a point estimate and a standard deviation. The estimated model presents a good fit: $\chi^2(4) = 13.85$ (SD=.92), p= .01, CFI=.99 (SD=.00), RMSEA=.02 (SD=.00), SRMR within = .01 (SD=.00), SRMR between = .02 (SD=.00). In Tables 4 and 5, we report the main parameters of the model, as well as the indirect effects decomposition. The estimates for the controlled variables are available upon request.

Main effects on math achievement. Relative differences between students' SES within school were positively related to math achievement (b=4.62, SE=.95, p<.01). Likewise, schools with an intake showing a higher mean SES also achieved higher scores (b=26.82, SE=5.00, p<.01). This factor presents a contextual effect of 22.20 points of difference in mathematics achievement for every point increase of school mean SES (SE=5.01, p<.01). Additionally, other school factors accounted for overall math achievement. Private schools reach 33.50 points more over the grand mean (SE=14.80, p=.02). Schools with higher academic emphasis also could be expected to have higher scores (b=3.58, SE=1.33, p<.01). No other school level factors present significant effects.

Students' sex and age explained some of the differences in math achievement. In general, female students presented lower scores than male students (b=-22.44, SE=2.85, p<.01). Students older than expected also presented lower scores than the rest of the population (b=-38.84, SE=3.27, p<.01).

Indirect effects. We decomposed the total and indirect effects estimates of Bullying on Math Achievement. These indirect estimates were significant only at the within part of the model. There were overall negative indirect pathways from bullying to achievement (b=-2.07, SE=.52, p<.01). These indirect effects were carried via our more proximal mediator, namely students' engagement (b=-1.15, SE=.34, p<.01). Additionally, there was a negative indirect effect via belonging which itself is related to mathematics achievement via classroom engagement (b=-.98, SE=.21, p<.01). Finally, the indirect effect via classroom engagement was conditioned by students' belonging levels (LMM=.48, SE=.17, p<.01), such that the indirect effect was larger when students had lower levels of belonging (-1SD, b=-1.29, SE=.29, p<.01) and smaller when students had higher levels of belonging (+1SD, b=-.68, SE=.15, p<.01). Thus, it seems students' sense of belonging with their school appeared to buffer the negative effects of bullying experience.

Table 4 MSEM main estimates, unstandardized

			Within			Between		
Parameter			E	(SE)		E	(SE)	
Engagement	⇒	Math	6.01	(.91)	***	5.84	(7.23)	
Bullying	⇒	Math	-.55	(2.24)		-63.88	(45.68)	
Belonging	⇒	Math	-.32	(2.63)		41.01	(22.21)	
SES	⇒	Math	4.62	(.95)	***	26.82	(5.00)	***
Belonging	⇒	Engagement	.89	(.05)	***	5.63	(5.65)	
Bullying * Belonging	⇒	Engagement	-.43	(.11)	***	-38.08	(51.73)	
Bullying	⇒	Engagement	-.19	(.05)	***	1.13	(1.73)	
SES	⇒	Engagement	.04	(.02)		-.29	(.52)	
Bullying	⇒	Belonging	-.18	(.02)	***	-.18	(.26)	
SES	⇒	Belonging	-.01	(.01)		-.09	(.03)	**
SES	⇒	Bullying	-.01	(.01)		-.03	(.02)	
Belonging	⇐ ⇒	Bullying * Belonging	.03	(.01)	**	.00	(.00)	*
SES	⇒	Bullying * Belonging	-.01	(.01)		-.02	(.01)	

Note * p<.05; ** p<.01; *** p<.001, ⇒ express regression coefficient, ⇐ ⇒ expresses a covariance estimation.

Table 5 MSEM Indirect effects

Indirect Effect Decomposition		Within E	Within (SE)		Between E	Between (SE)
Bullying	Total	-2.62	(2.23)		-70.54	(49.67)
	Indirect	-2.07	(.52)	***	-6.66	(14.41)
	Engagement	-1.15	(.34)	**	6.75	(13.61)
	Belonging	.06	(.48)		-7.35	(11.46)
	Belonging ⇒ Engagement	-.98	(.21)	***	-6.06	(13.56)
	Direct	-.55	(2.24)		-63.88	(45.68)
	LMM	.48	(.17)	**	41.28	(100.39)
Belonging	Total	5.03	(2.30)	*	74.79	(52.02)
	Engagement	5.35	(.90)	***	33.78	(55.98)
	Direct	-.32	(2.63)		41.01	(22.21)

Note * p<.05; ** p<.01; *** p<.001, ⇒ express regression coefficient, ⇐ ⇒ expresses a covariance estimation.

Discussion

Our first research question referred to the contextual effect of bullying on academic achievement. In the present study, we found evidence in favour of such a contextual effect. Specifically, schools with higher levels of bullying presented lower math achievement, regardless of students' individual experience of bullying. However, when we controlled for school safety, discipline and academic emphasis, this contextual effect was no longer significant. Thus, the contextual effects of bullying on math achievement seem to be explained by other observed characteristics of the school environment.

Our second line of inquiry concerns the indirect effects of bullying on achievement, via socio-motivational processes. Our results support this assumption: students who experience bullying showed lower math achievement, but this link is explained by students' engagement. Specifically, students who suffer bullying were less engaged with lesson, this in turn was predicted by lower levels of engagement/belonging with respect to their school as a whole. Moreover, the indirect pathway via classroom engagement was also *moderated* by the level of students' sense of school belonging: students with higher belonging presented a smaller indirect effect of bullying on achievement, in comparison to students with average levels of belonging.

Our results are consistent with previous findings. Bullying does appear to have negative contextual effects on achievement (Engel et al., 2009; Konishi et al., 2010; Román & Murillo, 2011), but these effects cease to appear once other school differences are accounted for. Academic emphasis, safety, and orderly environment are known effectiveness factor for school achievement (Mullis et al., 2012). Bullying event rates may have indirect effects on school academic achievement, via their relationship with school safety and discipline, as a bottom-up effect (Preacher et al., 2010). We did not test such model specifications regarding the interplay with covariates, but this is a line of research which would serve to illustrate how bullying contextual effects may work, via other observed school characteristics. Nonetheless, we can conclude from the present results that school-level variations in bullying serve as a meaningful predictor of school differences in achievement. However, these school differences seem to be accounted by variations in broader school characteristics regarding levels of safety and discipline.

In contrast, the within-school link between individual experiences of bullying and achievement seems to be explained by its relation to socio-motivational processes. Our results are consistent with previous authors' models and suggestions (Buhs et al., 2006, 2009; Mehta et al., 2013; Wormington et al., 2016), in which bullying is depicted as a stressful factor that diminishes school belonging, which in turn diminishes students' engagement with school lessons and thus is negatively related to academic achievement. Furthermore, we find positive evidence for the buffer effect of school belonging (Konishi et al., 2010), even with a different set of measures. Konishi and colleagues (2010) assessed school engagement via students' and teachers' relationships, whereas in the present study we use a direct measure of students' sense of belonging with their school. But our results are consistent in showing that those schools which manage to promote higher levels of school belonging for all their students may also manage to diminish the negative impact that bullying has on individual students' motivation and therefore achievement.

This study has some limitations due to its design, and due to its model specification. First, because of its design, these results generalize to the target population of students at grade 8th from Chile, defined by TIMSS 2011 study. Thus, these results may not generalize to other contexts and other age cohorts. Nevertheless, Wormington and colleagues (2016) compared a similar model in which school belonging was the mediator of the effects of peer victimization and school achievement in two different samples from middle school and high school, and found no large differences for these two age groups. To robustly test the proposed model on different ages and different context, this same model can be fitted across all countries that participated in TIMSS 2011, 2015 and 2019, and similarly, can be fitted onto the 4th grade samples. This future work would provide further evidence regarding the generalizability of the proposed model.

In the present study we assess if the bullying path to engagement, is heterogenous to different levels of student sense of belonging. Our present model specification can assert this relation, the bullying path to engagement is not constant across schools. However, we are assuming this interaction is of a linear type. That is, that bullying, and engagement relations can be larger or smaller, conditional to levels of students sense of belonging, but we are not assessing if this heterogeneity has a different shape. Moderation, can be linear, non-linear, and there are different approaches to study moderation besides the use of product terms as we have done here, including latent moderated equations and quasi-maximum likelihood approaches (which does not rely on normality assumptions of interacting terms) (Marsh et al., 2009). Further research is needed regarding this moderation, because is important to identify what levels of senses of belonging needs to be promoted to achieve the intended buffer effect on bullying experience.

Because of the current model specification, we have paid no attention to gender differences for this model. There is a substantial literature within the bullying and peer victimization research indicating that gender plays an important role in this phenomenon. For example, boys tend to be more involved in physical bullying, whereas girls tend to be more involve in relational bullying (Berger et al., 2008). Moreover, peer rejection is more predictive of victimization for girls, but not for boys, in schools with higher bullying (Isaacs et al., 2013), and so some contextual effects are already known to be different for boys and girls. Females students also seem to be more at risk of suicide related to bullying (Bauman et al., 2013; Hertz et al., 2013). These are just a few examples of gender differences and bullying dynamics. In future research, we aim to separate physical and relational bullying, similarly to Contreras et al (2015), in order to estimate if the gap between each type of bullying is similar for boys and girls.

Studies targeting bullying as an outcome frequently inform efforts to prevent this behaviour and to identify more at-risk populations. The present work provides information regarding the psychological mechanisms that serve as plausible causal links between the experience of bullying and poorer academic achievement. By means of understanding how aversive events such as bullying are linked to different school adjustment outcomes, interventions can target the specific mechanism by which bullying exerts its influence on school outcomes (Wormington et al., 2016). This is informative, not only for prevention, but for interventions as well. An example of this later line of research was conducted by Norwalk and colleagues (Norwalk et al., 2015). In this study, school belonging was indirectly related to teacher attunement with respect to student victimization. This is a specific type of teacher responsiveness and refers to how much teachers know about their students' bullying dynamics (e.g., who is being bullied in different ways). Schools with higher attunement also tend to have students with less tolerance for bullying, thus creating a protective peer environment which in turn explains school belonging. Thus, while the present research shows that a broad measure of students' emotional engagement with the school context (feeling that they belonged, feeling safe, and liked their school) played a role in the indirect pathways of relations between bullying and math achievement. Much more needs to be done to untangle the variables that give rise to this sense of belonging in the first place.

In summary, our work sets an agenda for research on school bullying as a pervasive phenomenon across schools. We have shown that most of its relations with academic achievement are of an indirect nature. Thus, univariate approaches and conventional model specifications may not adequately capture its relations on outcomes under study, by ignoring its relations to other variables, by ignoring its contextual effects, or by merely centering the attention on "significant [main] effects". Careful consideration of model specification is essential in this regard, as subtle changes in how to include covariates can lead to different conclusions based on the same data. Our results point to the need to account not only for contextual covariates to understand school-level variations, but also indirect and interaction effects involving socio-motivational factors to understand within-school effects of bullying on students' achievement.

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