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DO PROFESSIONAL LEARNING COMMUNITIES MATTER FOR STUDENT ACADEMIC PERFORMANCE? AN ANALYSIS OF DATA FROM THE ECLS-K

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For my mother, Patricia Caton, who has always believed in me

more than I've believed in myself.

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ABSTRACT

The purpose of this study is to examine the effect of professional learning communities (PLCs) on elementary school students' performance in reading and mathematics using data from the Early Childhood Longitudinal Study, Kindergarten Cohort of 1998 (ECLS-K). This study also investigates whether PLCs have differential effects on student performance based on student characteristics such as socioeconomic status (SES), race, and whether they are academically at-risk and school characteristics such as school type, school size, minority enrollment, and percentage of students eligible for free or reduced-price lunch (FRPL). PLCs are seen as a promising way of remedying the traditionally isolated nature of teachers' work by facilitating a network through which teachers can share expertise, receive support, and disseminate effective practices. The underlying theory is that by facilitating teachers' access to a network of their peers, they will be able to improve their instruction, which will ultimately lead to improved student achievement. This study addresses the need for more empirical evidence on the impact of PLCs on student performance using a large, national dataset. Principal component analysis (PCA) was used to identify correlated PLC items from the ECLS-K teacher questionnaire. Hierarchical and cross-classified random effects modeling (HCM) was then used to analyze the impact of student-, teacher-, and organizational-level variables—including two PLC variables—on students' reading and mathematics performance. The analysis found that teacher collaboration had a significant positive effect on growth in reading and math scores, while a positive school climate was associated with significantly higher initial reading scores. Rarely did either PLC variable show differential effects based on student- or school-level characteristics.

CHAPTER 1

INTRODUCTION

Background of the Study

Teachers' work in the United States has traditionally been a private endeavor, occurring behind the classroom door with limited interaction with colleagues (Lortie, 1975; Rosenholtz, 1989; Sarason, 1996). Describing the history of teaching in America, Lortie (1975) explains that teachers have generally worked in isolation from their colleagues physically, socially, intellectually, and psychologically. While this was unavoidable when teachers taught in one-room schoolhouses far from schools in other communities, teachers today still primarily work separated from their colleagues, even as they teach under the same roof.

There is growing awareness, however, that facilitating teacher learning is essential to enhancing student learning (Sarason, 1996). Toward that end, researchers, policymakers, and practitioners have recognized the value of a more collaborative teaching corps. The education community, including the U.S. Department of Education, has emphasized professional learning communities (PLCs) as an important way to create a more collaborative working environment for teachers. For example, when Congress reauthorized the Elementary and Secondary Education Act (ESEA) in December 2015, the law reflected the importance of the essential features of PLCs for teachers' professional development. Specifically, Congress redefined professional development as activities that

> (A) are an integral part of school and local educational agency strategies for providing educators … with the knowledge and skills necessary to enable students to succeed in a well-rounded education and to meet the challenging State academic standards; and (B) are **sustained (not stand-alone, 1-day, or short term workshops), intensive, collaborative, job-embedded, data-driven, and classroom-focused**. (S. 1177, Section 8002, page 295, paragraph 42. Emphasis added.)

The ESEA definition of professional development does not reflect a top-down mandate for a more collaborative teaching profession. Rather, there is evidence that teachers want to establish closer working relationships with their colleagues (*Primary Sources*, 2012). Discussing this provision of ESEA, Megan Wolfe, the government relations manager for the Association for Supervision and Curriculum Development (ASCD), stated, “What [teachers] want is for their schools to provide this kind of job-embedded learning, with opportunities to collaborate with colleagues throughout the year, so they can begin to apply their learning immediately in ways that are meaningful and relevant” (Pierce, 2016, n.p.).

Advocates of PLCs extol their benefits for teachers and students. In general, researchers theorize that PLCs directly improve teacher performance, thereby indirectly improving student performance. More specifically, research has shown that PLCs work through a variety of mechanisms that include reducing the stress and burnout caused by teachers’ isolation (Lee & Smith, 1996), increasing social support for teacher learning (Louis & Marks, 1998), increasing teacher commitment and effort (Darling-Hammond, 2010; Little, 1990), creating a greater sense of individual and collective efficacy among teachers (Louis & Smith, 1992; McLaughlin & Talbert, 1993; Moolenaar, Sleegers, & Daly, 2011; Rosenholtz, 1989), and improving instruction (Louis & Marks, 1998; McLaughlin & Talbert, 1993; Pil & Leana, 2009; Tschannen-Moran, 2009).

Statement of the Problem

The research on PLCs is deeply rooted in the work of school reform and effective schools research, which examines the organizational features of schools that are important factors in school success. PLCs challenge the traditional model of schools where teachers work in relative isolation from their colleagues (Lee & Smith, 1996). This professional isolation is considered by many in the education community to be a barrier to teacher learning and effective practice, and therefore, increased student achievement (Lortie, 1975; Sarason, 1996). PLCs are seen as a promising way of remedying teacher isolation by facilitating a network through which teachers can share expertise, receive support, and disseminate effective practices. The underlying theory is that by facilitating teachers' access to a network of their peers, they will be able to improve their instruction, which will ultimately lead to gains in student achievement.

PLCs create ongoing, work-embedded professional development that allows teachers to access the knowledge and skills of their colleagues and apply what they learn to their own practice with the ultimate goal of improving student learning. By bringing colleagues together to discuss and collaborate on practice, PLCs are believed to give teachers opportunities to build upon each other's knowledge of content, pedagogy, and students. Working closely with one another, teachers can seek new ideas and support from each another while sharing their own knowledge and experience about effective practice. While researchers have used different definitions of PLCs, this study relies on five essential features described by Kruse, Louis, and Bryk (1995):

1) Shared values
2) Reflective dialogue
3) Deprivatization of practice
4) Collaboration
5) A focus on student learning

According to Kruse, Louis, and Bryk, members of a PLC must have a common belief system about teaching and learning (1995). While they do not need to agree on every issue, they must share a general orientation toward critical education policies and practices. They must engage in honest and ongoing discussions about teaching and learning, open their practice to peer observation and feedback, and work closely with their fellow teachers to improve teaching practices, curricula, and school policies (1995). Finally, the end goals of PLCs must center on improved student learning (1995).

Purpose of the Study

The literature on PLCs assumes that increased collaboration and access to a network of peer expertise will lead to subsequent improvements in student outcomes. Is there empirical evidence to support this assumption? The purpose of this study is to answer this question by examining the effect of PLCs on elementary school students' performance in reading and mathematics using data from the Early Childhood Longitudinal Study, Kindergarten Cohort of 1998 (ECLS-K). This study also investigates whether PLCs have differential effects on student performance based on student characteristics such as socioeconomic status (SES), race, and whether they are academically at-risk as well as school characteristics such as school type, school size, minority enrollment, and percentage of students eligible for free or reduced-price lunch (FRPL). As noted earlier, researchers theorize that PLCs affect student achievement indirectly through a variety of mechanisms such as reduced stress and burnout caused by isolation, increased social support for teacher learning, increased teacher commitment and effort, a greater sense of individual and collective efficacy, and improved instruction. Multilevel models are used to answer this study's research questions.

Research Questions and Hypotheses

This study answers the following research questions:

1) What is the effect of PLCs on elementary students' performance in reading and mathematics?

2) Do PLCs have differential effects on students' reading and mathematics performance based on the following student characteristics: SES, race, and at-risk status?
3) Do PLCs have differential effects on students' reading and mathematics performance based on the following school characteristics: school type, school size, minority enrollment, and percentage of FRPL-eligible students?

Prior research examining the impact of PLCs on student achievement has generally shown small but significant positive effects. For example, in their meta-analysis of five quantitative studies, Lomos, Hofman, and Bosker found effect sizes that ranged from small to medium (2011). The pooled effect of the five studies was small but significant and driven primarily by the relative weight of a 1996 study by Lee and Smith. In light of this research and the lack of information on the specific nature and quality of the teacher interactions in PLCs in the current study, my hypothesis is that PLCs will have a small but significant effect on elementary school student performance. I further hypothesize that PLCs will have differential effects on students with the greatest effects observed for middle-class students, white students, and students who are not considered academically at-risk. I also hypothesize that public schools, larger schools, schools with higher minority enrollment, and schools with higher percentages of FRPL-eligible students will reduce the influence of PLCs on student performance.

Overview of Methodology

The current study analyzes data from the ECLS-K. In 1998, the ECLS-K began following a nationally representative sample of kindergarteners providing researchers, policymakers, and other stakeholders with a comprehensive set of data on students' development and experiences from kindergarten through elementary and middle school. The data allow for a better understanding of "how various child, home, classroom, school, and community factors at various points in children's lives relate to cognitive, social, emotional, and physical development" (National Center for Education Statistics [NCES], n.d.). Given the breadth and depth of its national data collection, data from the ECLS-K provide a prime opportunity to study PLCs and their impact on students. The ECLS-K is a multi-source, multi-method longitudinal study comprising data about students, parents, teachers, and administrators across the United States. It is designed to provide reliable data on a cohort of students and the multitude of factors that affect students' academic, social, emotional, and physical health-related outcomes. The sample comprises students from public and private schools and diverse socioeconomic, racial, and ethnic backgrounds. The study design provides researchers the ability to link student-level data to data on families, teachers, and schools on a vast array of topics including PLCs.

The current study first used principal component analysis (PCA) to examine the correlations among items in the teacher questionnaire that reflect elements of PLCs. PCA is useful for simplifying interrelated measures, such as multiple items from a questionnaire, by identifying correlations among them. This is recommended for purposes of parsimony and error reduction and to help build and confirm theory (Child, 1990; Thompson, 2004).

Once PCA helped to identify correlated items from the teacher questionnaire, hierarchical and cross-classified random effects modeling (HCM) was used to analyze the impact of student-, teacher-, and organizational-level variables, including PLC variables, on students' reading and mathematics performance. The HCM analysis in this study relies on data from a variety of ECLS-K sources including student performance in reading and mathematics from the direct child assessments, student-level data from the parent interview, teacher-level data from the teacher questionnaire, and school-level data from the administrator questionnaire. Weights were applied during the HCM phase of analysis to account for the complex sampling design and estimate findings for the cohort of students who entered kindergarten in 1998-1999 or first grade in 1999-2000 rather than reporting on only those students sampled for participation in the ECLS-K.

HCM is an appropriate analytical tool to answer the research questions because it can account for the naturally-existing, nested structure of schools. Students in the same classroom are expected to have outcomes more similar to one another than to students in other classrooms (Raudenbush & Bryk, 2002). The same can be said for students and teachers in the same school. Moreover, HCM can account for students' mobility across grades. Traditional hierarchical linear modeling (HLM) can only handle hierarchical data structures where one lower-level unit is nested in one higher-level unit—for example, when each student is a member of only one classroom (Raudenbush & Bryk, 2002). Due to the longitudinal nature of the data in the current study, students were taught by multiple teachers during their elementary school years. As a result, each student is nested in multiple classrooms thereby violating a necessary condition of HLM.

Significance of the Study

The findings from this study contribute to the field in several ways. First, the research addresses the need for more empirical evidence on the impact of PLCs on student performance using a large, national dataset. Research on the effects of PLCs has primarily been descriptive with few studies examining their impact on instructional practices or student achievement (Lomos et al., 2011; Stoll, Bolam, McMahon, Wallace, & Thomas, 2006; Vescio, Ross, & Adams, 2008). Studies that have examined the impact on student achievement are often restricted to a single school or school district and do not link student data to teacher data, thereby limiting generalizability.

Second, the research examines how PLCs affect various student populations differently, an area not fully explored in previous research. Previous research has demonstrated the powerful effect of student characteristics, particularly family income, on school achievement (Coleman, 1966; Reardon, 2011). In addition, Lomos et al. (2011) suggest that the positive effects of PLCs may be due to facilitating organizational factors. Research has been conducted on how some organizational characteristics facilitate or impede PLCs, but there is no clear consensus in terms of characteristics such as school type and size, and limited research on minority enrollment and school-level FRPL eligibility. This research addresses the gap in the literature on organizational characteristics that may mediate the effect of PLCs.

Finally, several important organizations in the education field have emphasized the importance of collaborative working environments for teachers and the benefits of teacher collaboration for students, including the National Board for Professional Teaching Standards (NBPTS) and Learning Forward (formerly known as the National Staff Development Council). The NBPTS is the independent nonprofit organization that created National Board Certification, the highest professional certification that teachers can achieve. Learning Forward is the largest nonprofit membership association for teacher professional learning. Both organizations include participation in learning communities in their key standards for teacher practice. Moreover, in the most recent reauthorization of the ESEA, the U.S. Department of Education specified that teacher professional development be "intensive, collaborative, job-embedded, data-driven, and classroom-focused," essential features of PLCs (S. 1177, Section 8002, p. 295, paragraph 42). Although there appears to be agreement coalescing around a need to better support teachers and schools in their efforts to improve student learning, more research on effective ways to provide that support is still needed.

Limitations of the Study

This study is limited to an examination of data from kindergarten through fifth grade due to the omission of PLC items from the teacher questionnaires during the eighth-grade data collection of the ECLS-K. The analytic samples are restricted to data from students while they remained in the school where they were initially sampled. For example, if a student changed schools in third grade, data from kindergarten and first grade were used in the analysis. Fifth-grade students who were randomly assigned to have their science teacher as opposed to their mathematics teacher complete a questionnaire were also excluded from the mathematics analysis. If the students who were excluded from the study are systemically different from the students who were included, the analysis may be biased and no longer representative of the population. This would affect the conclusions that can be drawn from the analysis.

Due to the constraints of using data from a study not specifically designed to examine PLCs, the set of questionnaire items included in the study may not fully capture all dimensions of PLCs. For example, there were three yes/no items in the early rounds of data collection that asked teachers about deprivatized practices such as peer observation, but these items were dropped after the spring first-grade data collection and therefore not included in this study. Additionally, a few of the questionnaire items reflect concepts that some researchers consider related to but distinct from PLCs (Louis & Marks, 1998). For example, the items on how much influence teachers have over school policy and how much control they have in their classroom over instruction and discipline could be considered to reflect distributed leadership rather than PLCs. This study also relies on teachers' self-reported PLC-related activities, and the specific nature of these activities is not clear.

Directions for Future Research

Directions for future research are based on this study's limitations. First, national studies examining the effects of PLCs with more robust data on the characteristics of PLCs are needed. The ECLS-K included teacher questionnaire items indicative of PLCs, but PLCs were not a specific focus of the study. As a result, important dimensions on PLCs, such as deprivatization of practice, were not included in the analysis. Second, this study excluded from the analysis students who changed schools during the data collection period. If these students are different from their peers in meaningful ways, bias may be introduced into the analysis. Future research on PLCs should include school-changers in the analysis to avoid the introduction of selection bias. Finally, this study uses data from the 1998 ECLS-K. The 2011 ECLS-K, currently in progress, does not include PLC items on the teacher questionnaires. An analysis of more recent data is needed, particularly in light of the continued emphasis on policies that promote more collaborative, job-embedded professional development for teachers.

CHAPTER 2

LITERATURE REVIEW

Introduction

This chapter provides an examination of literature relevant to the study. The literature review begins with an overview of the isolated nature of teaching in America and its effects on teachers and students. This is followed by a discussion of the difficulty of enacting reform through bureaucratic measures. Together, these sections of the literature review provide organizational context for PLCs. The concept of PLCs is then introduced, addressing their defining characteristics, theory of change, and challenges to their conceptualization and implementation. Finally, the literature review discusses gaps of knowledge in the literature—specifically, limited empirical research on the impact of PLCs on student achievement—and the significance of this study considering those gaps.

Teacher Isolation

Teachers' work in the United States has traditionally been antithetical to the collaborative, collegial nature of PLCs. Teaching has typically been a private endeavor, occurring behind the classroom door with limited interaction among colleagues (Lortie, 1975; Rosenholtz, 1989; Sarason, 1996). In his seminal work, *Schoolteacher: A Sociological Study*, Lortie argues that "throughout the long, formative decades of the modern school system, schools were organized around teacher separation rather than teacher interdependence" (1975, p. 14). In support of his argument, Lortie provides historical background on the teaching experience in the United States, beginning with the colonial period. At that time, teachers were assigned to one-room schoolhouses in distant and often remote settlements (1975). As a result, teachers had very little, if any, contact with other teachers.

As the population in the United States grew and became more urban, multiple teachers began teaching under the same roof (Lortie, 1975). Despite the new organizational arrangement, teachers continued to work in relative isolation (Lortie, 1975; Davis, 1987). Lortie emphasizes this disconnectedness among teachers by describing schools as an “egg crate,” with teachers physically separate from one another in individual classrooms and working independently. It is this isolation that led Levine to refer to teaching as “a lonely profession” (Sarason, Levine, Godenberg, Cherlin, & Bennett, 1966, p. 74).

Despite the current rhetoric in the education community and among policymakers extolling the virtues of collegiality and collaboration, descriptions of American teachers’ professional isolation remain salient today. In a study on school-based social networks, Atteberry and Bryk call teacher isolation the norm (2010). Empirical evidence supports this view. In a recent report on teacher professional development in the United States and abroad, Darling-Hammond and colleagues analyzed data from the Schools and Staffing Survey (SASS) and the National Staff Development Council (NSDC). They found low levels of teacher collaboration, a major component of PLCs, in most American schools with little emphasis on teacher collaboration in professional development (Darling-Hammond, Wei, Andree, Richardson, & Orphanos, 2009). The authors note that this stands in contrast to professional development in higher-performing European and Asian countries where a considerable amount of collaborative professional learning is structured into teachers’ daily work (2009).

Furthermore, a national survey of public school teachers sponsored by Scholastic and the Gates Foundation found that a lack of time to collaborate with colleagues was the second most frequently-cited challenge selected by half of the teachers in the study (*Primary Sources*, 2014). A larger percentage of respondents cited this as a challenge as opposed to other issues such as large class sizes, limited earning potential, and not enough instructional time. Only constantly changing demands on teachers and students was cited by a larger percentage of respondents. In an earlier iteration of the survey, respondents indicated that, on average, they spend just 15 minutes of the work day collaborating with colleagues (*Primary Sources*, 2012).

Why does this matter? Researchers argue that the physical and social isolation that teachers experience leads to intellectual and psychological isolation (Lortie, 1975). Professional isolation has been indicted as a barrier to teachers' continuous learning and effective practice because it constrains the resources teachers have available to them and their professional development (Little, 1982; Lortie, 1975; Rosenholtz, 1989). There are few opportunities for teachers to share reflections about their practice and even fewer opportunities to observe and provide feedback on each other's practice as they would in a PLC (Davidson & Dwyer, 2014). When teachers are disconnected from one another, it can prevent diffusion of new knowledge and implementation of new programs because teachers do not have a strong influence over each other's work (Atteberry & Bryk, 2010). Moreover, according to Levine and Marcus, "Asking for help can be difficult in a culture that values autonomy; similarly, teachers may not be comfortable offering suggestions to other teachers or sharing their own practice publicly" (2007, p. 129).

In addition to the intellectual isolation described above, researchers have noted that teachers can show psychological feelings of distress due to being disengaged from their colleagues (Davidson & Dwyer, 2014; Flinders, 1988; Sindberg & Lipscomb, 2005). Davidson and Dwyer cite research by Rogers and Babinski (2002) indicating that teachers' levels of stress rise when they do not receive constructive feedback on their practice. This can lead to feelings of helplessness and professional burnout (Gaikwad & Brantley, 1992). These feelings are not confined to the minds of individual teachers; rather, they can have profound systemic effects. For example, the national survey of teachers sponsored by Scholastic and the Gates Foundation found that resources such as supportive leadership and time for collaboration with colleagues, elements related to PLCs, mattered more for teachers' job satisfaction and retention than higher salaries (*Primary Sources*, 2012). Moreover, nine in ten teachers indicated that time to collaborate with peers was "absolutely essential" or "very important" for teacher retention (2012).

In some ways, the physical and social organization of schools can be viewed as adaptive (Flinders, 1988; Lortie, 1975; Ostovar-Nameghi & Sheikhahmad, 2016). For example, Lortie notes that for most of the teaching profession's history, the majority of teachers were single, unmarried women (1975). When they left the profession to marry and start a family, the impact of teacher attrition was lessened because teacher interdependence was limited. According to Ostovar-Nameghi and Sheikhahmad, teacher isolation can also be protective for the teachers themselves, insulating teachers from external interference (2016). Moreover, they note that what is negatively viewed by some teachers as isolation is positively viewed by others as autonomy (Ostovar-Nameghi & Sheikhahmad, 2016). However, the case has been made that the negative effects of teacher isolation outweigh any benefits.

The Limits of Bureaucracy

Bidwell's 1965 article "The School as Formal Organization" has been described as "marking the beginning of serious attempts to understand the organizational nature of schools" (Allison, 1983, p.15). Bidwell discusses bureaucratic characteristics of schools such as the division of labor, hierarchical staff roles, and operating rules and regulations (1965). He explains that the underlying assumption of school systems is that they are at least to some degree rational because they are expected to achieve some minimum standard of output and because of the huge scope and complexity of the task of educating students.

On the other hand, Bidwell and others note a “structural looseness” to schools that makes it difficult to control what is often referenced as the technical core (i.e., instruction) through bureaucratic measures (Bidwell, 1965; Gamoran & Dreeben, 1986). Bidwell ties this structural looseness (or autonomy) to the nature of the teaching task itself; teachers often teach students who have a range of skills and abilities in a dynamic and somewhat uncertain classroom environment. Therefore, they require a certain degree of autonomy to respond in real time. Ostovar-Nameghi and Sheikhahmad’s view that teacher isolation can be framed as autonomy reflects Bidwell’s depiction of schools in which teachers have considerable discretion over instruction (2016). Similarly, researchers such as Hargreaves (2000), Rowan (1994), and Tschannen-Moran (2009) have argued that teaching, due to its complexity and uncertainty, requires a great deal of flexibility and space for professional judgment.

The discussion above suggests ways that bureaucratic models of organizations can be problematic when applied to schools and other organizations. This is often cited as one of the reasons why school reforms, which rely heavily on bureaucratic measures of control, fail: the link between policy and the classroom can be tenuous (Elmore, 2004; Rowan, 1994). However, there is a distinction between isolation and autonomy, and teachers can retain a level of autonomy while still participating in PLCs, a more relational—and potentially more effective—form of social control.

Professional Learning Communities (PLCs)

PLCs are viewed as a promising way to remedy teacher isolation through a built-in support network that teachers can turn to for expertise and support, thereby changing the culture of schools (Fullan & Hargreaves, 1991; Lee & Smith, 1996; Levine & Lezotte, 1990). Speaking to both the intellectual and psychological effects of teacher isolation, Moolenaar and Seegers state, “Strong teacher networks enhance the dissemination of information on schoolwide reform efforts, an open orientation toward innovation, and overall school functioning, as well as counteract negative phenomena such as absenteeism and low job satisfaction resulting from teacher isolation” (2010, p. 99). At the heart of the PLC concept is the importance of regular, collaborative interactions among colleagues for ongoing teacher learning and morale, which ultimately benefits students (Talbert & McLaughlin, 1993).

PLCs operate under the assumption that the key to improving learning for students is continuous, job-embedded learning and professional development for educators (DuFour, Dufour, & Eaker, 2008). Research has shown that intensive, sustained teacher professional development closely connected to instructional practice has a greater likelihood of improving teacher practice and therefore student achievement (Desimone, Porter, Garet, Yoon, & Birman, 2002; Darling-Hammond et al., 2009). This model of professional development is evident in the reauthorization of ESEA (2015). As stated in chapter one, the law defines professional development as activities that

> (A) are an integral part of school and local educational agency strategies for providing educators … with the knowledge and skills necessary to enable students to succeed in a well-rounded education and to meet the challenging State academic standards; and (B) are sustained (not stand-alone, 1-day, or short term workshops), intensive, collaborative, job-embedded, data-driven, and classroom-focused…

Discussing this provision of ESEA, Megan Wolfe, the government relations manager for the ASCD, stated: “What [teachers] want is for their schools to provide this kind of job-embedded learning, with opportunities to collaborate with colleagues throughout the year, so they can begin to apply their learning immediately in ways that are meaningful and relevant”

(Pierce, 2016, n.p.). Stephanie Hirsh is the executive director of Learning Forward, the largest nonprofit membership association for teacher professional learning. On the organization's website, she expressed her pleasure about the law's explicit focus on professional development opportunities that are "sustained…, intensive, collaborative, job-embedded, data-driven, and classroom focused'" (Learning Forward, 2015, n.p.). She states, "Our standards have outlined these elements for close to two decades. Sadly, the professional development that many educators in our country experience doesn't include these components, nor the other conditions and structures essential to professional learning that ultimately helps the students in our schools" (Learning Forward, 2015, n.p.). In addition to Learning Forward, Leonard and Leonard (2003) note other influential educational organizations that emphasize the importance of collaborative working environments for teachers and their benefits to students, including the National Board for Professional Teaching Standards (NBPTS) and the Council of Chief State School Officers (CCSSC, formerly known as the Interstate School Leaders Licensure Consortium).

Broadly, Bolam et al. describe an effective PLC as having "the capacity to promote and sustain the learning of all professionals in the school community with the collective purpose of enhancing pupil learning" (2005, p. iii). More specifically, Louis and Marks state:

> Five elements of practice typify schoolwide professional community: shared values, focus on student learning, collaboration, deprivatized practice, and reflective dialogue. These elements are not a hierarchy, but their presence distinguishes professional community that is schoolwide from other forms of school cultures (1998, p. 539).

Many researchers have relied upon these elements to define PLCs (Kruse et al., 1995; Lomos et al., 2011; Stoll et al., 2008). Kruse et al. (1995) describe the five elements in more detail:

1) Shared values. This is a foundational feature of PLCs. PLCs have shared beliefs about instructional purposes, practices, and behaviors, although this does not imply full consensus on every issue (p. 29).

2) Reflective dialogue. PLCs are defined by their communication about practice, pedagogy, and student learning. The authors consider this the bridge between shared beliefs and improved practice (p. 30).
3) Deprivatization of practice. PLCs involve the practice of improving teaching through observation and peer coaching. This element relies upon an open and honest discourse among teachers about their own and each other's teaching (p. 31).
4) Focus on student learning. PLCs involve a keen focus on how instructional techniques affect student learning so feedback about the effects of teaching practice on student learning is key. The belief that all students are capable of learning is also critical (p. 32).
5) Collaboration. A range of activities fall under this element. As PLCs mature and strengthen, participants move from cooperation to collegiality to collaboration, the essence of which is the co-development of instructional materials (p. 33).

These five elements are reminiscent of Little's earlier research on "the critical practices of adaptability" (1982, p. 332). In her case study of six elementary schools, Little investigates the organizational features conducive to teacher learning on the job. She finds that continuous professional development occurs most when teachers engage in frequent, continuous, and concrete talk about teaching practice (i.e., reflective dialogue); are frequently observed and receive useful feedback on their practice as well as teach each other practice (i.e., deprivatization of practice); and plan, design, and evaluate materials together (i.e., collaboration).

Some researchers have included other elements such as shared decision making or supportive leadership as part of the PLC concept, while other researchers view these as facilitators of PLCs rather than dimensions of the concept itself. For example, Lee and Smith (1996) conceptualize PLCs as consisting of collective responsibility among teachers for student learning (i.e., a focus on student learning), cooperation and support among teachers (i.e., collaboration), and teacher control over decisions pertaining to curriculum, pedagogy, schoolwide policies and professional development. This last element is not included among the characteristics described by Louis and Marks. In their conceptualization, Visscher and Witziers (2004) include consensus (i.e., shared values), consultation and cooperation (i.e., collaboration), policy and evaluation, decision making, and school and departmental leadership (similar to Lee and Smith's dimension on teacher control). Despite differences among researchers, there is still a great deal of overlap and congruence across their conceptualization and operationalization of PLCs with collaboration as a common thread.

Theory of Change

Researchers theorize that PLCs affect student achievement indirectly through a variety of mechanisms such as reduced stress and burnout caused by isolation (Lee & Smith, 1996), increased social support for teacher learning (Louis & Marks, 1998), increased teacher commitment and effort (Darling-Hammond, 2010; Little, 1990), a greater sense of individual and collective efficacy (Louis & Smith, 1992; McLaughlin & Talbert, 1993; Moolenaar, Sleegers, & Daly, 2011; Rosenholtz, 1989), and improved instruction (Louis & Marks, 1998; McLaughlin & Talbert, 1993; Pil & Leana, 2009; Tschannen-Moran, 2009). With respect to instruction, Vescio et al. (2008) note that the literature on PLCs view schools as learning organizations that are based on (at least) two assumptions: 1) knowledge is situated in the day-to-day experiences of teachers and 2) PLCs will enhance teacher professional knowledge and therefore improve student learning (p. 81). PLCs are posited as a source of ongoing, embedded professional development through which teachers learn from those who best understand the school's student population, curriculum, and instructional challenges—their colleagues. This is in contrast to traditional professional development models through which teachers receive external support that it is often too intermittent and variable to have a significant or lasting impact on their practice or student achievement (Halverson, 2003). Therefore, researchers like Grossman, Wineburg, and Woolworth (2000) emphasize the need for PLCs to be concerned with their clientele; in the case of schools, this means students. Research suggests that for PLCs to achieve observable positive student outcomes, the focus of the learning community's efforts must be aimed squarely on matters pertaining to instruction and limited to activities closely connected to classroom practice, such as lesson planning and decisions about curricula (Little, 1982; McLaughlin & Talbert, 1993).

Challenges to the Conceptualization and Implementation of PLCs

One of the major challenges to research on PLCs is conceptual (Lomos et al., 2011; Stoll et al., 2008). There is no universally agreed upon definition of PLCs; the concept is operationalized differently by different researchers and the notion of community is considered by many to be ill-defined (DuFour, 2004; Lomos et al., 2011; Stoll et al., 2008). Grossman and her colleagues posed a simple question: What distinguishes a group of teachers in a room together from a PLC? They argue that "groups of people become community, or so it would seem, by the flourish of a researcher's pen" (2000, p. 6). Similarly, Leonard and Leonard (2003) point out that collaborative activities can occur any time teachers talk about school matters, including discussions about administrative duties, but that is not sufficient to classify a "group of teachers in a room together" as a PLC. As DuFour (2004) notes, using the term PLC is not enough to confirm its existence.

Moreover, a great deal of descriptive research has been conducted on the implementation of PLCs, and the findings suggest that the process is complex. For example, PLCs push teachers to think about their practice in new ways (Vescio et al., 2008). Grossman et al. note that PLCs require a "new form of social and intellectual participation" that moves teachers away (sometimes uncomfortably so) from the traditional occupational norms of privacy (2000, p. 48). Learning from colleagues often requires a major shift in thinking for teachers who are used to being viewed as the authority in their classrooms and may be less comfortable assuming the role of student among their peers (Grossman et al., 2000).

Alternatively, teachers in PLCs must also serve as a source of expertise for their colleagues. The PLC model of professional development relies on what Cochran-Smith and Lytle called "knowledge of practice" in which expertise about teaching comes from within the school building, generated because of teachers' experiences in their classrooms, their reflections about practice, and their discussions with colleagues (as cited in Vescio et al., 2008, p. 89). This stands in contrast to the traditional professional development model that relies heavily on teachers acquiring "knowledge for practice" from experts external to the school building that teachers then apply to their work (Vescio et al., 2008, p. 89). Providing expertise to peers is considerably different from providing expertise to elementary and secondary students. Not all teachers can step into this role easily and without tension.

Grossman and her colleagues have a particularly unique perspective on implementation of PLCs because they not only conducted research on the topic, but they themselves worked to establish a PLC among secondary teachers in English and social studies over the course of two years (2000). Their work demonstrates the considerable time and energy that must be spent fostering the conditions for collaboration and a more professional orientation to their work, including how to raise and address conflicting points of view. Achinstein (2002) posits that conflict plays an important role in learning communities (2002). Multiple perspectives at the table enriches the discussion and builds the capacity of the learning community, but it also opens the door to conflict, especially factoring in the personal histories—not always pleasant—that colleagues have with one another. Conflict is not necessarily a bad thing; if handled openly and productively, conflict can facilitate change and innovation (Achinstein, 2002; Grossman et al., 2000). If everyone at the table agrees with everyone else, or is not comfortable expressing dissenting opinions, what may result instead is a reinforcement of the status quo.

Grossman and her colleagues' experience supports research that has found that structural aspects, such as time to meet, are necessary but insufficient facilitators of PLCs (Bryk, Camburn, & Louis, 1999; Bryk & Schneider, 2002; Louis, Marks, & Kruse, 1996). For example, social and human resources such as trust, respect, and openness to innovation among colleagues appear to exert a stronger influence on PLCs than structural conditions (Bryk, Camburn, & Louis, 1999; Bryk & Schneider, 2002; Louis, Marks, & Kruse, 1996). For example, Bryk and Schneider (2002) examined how relational trust facilitated implementation of school reform efforts in three Chicago elementary schools after the Chicago School Reform Act of 1988. They demonstrated that trust is a valuable resource in schools. Schools with a high level of trust at the beginning of reform had a one in two chance of improving student achievement compared to a one in seven chance for those schools that had low levels of trust (pp. 14-15). Similarly, Bryk et al.'s study examining the structural, human, and social factors supporting the development of PLCs also identified trust as a strong facilitator (1999). This evidence supports the work of Coleman (1988), who argues that trust helps people share ideas and knowledge, thereby boosting organizational capacity. To be clear, trust is a facilitating factor of PLCs, but it is not sufficient on its own.

Furthermore, researchers often describe PLCs as a way to build teachers' knowledge and expertise assuming that the information that teachers have is not redundant. However, researchers like Achinstein (2002) and Grossman (2000) caution that in-school networks of teachers can easily stifle creativity and innovation, thus reinforcing the status quo. Burt, who wrote extensively about social networks and social capital, acknowledges the benefits of a closed network emphasized by Coleman; for example, trust and credibility are easier to establish (2000). However, Burt argues that network closure can have negative consequences such as constraining the flow of new ideas and innovation (2000). Because PLCs rely heavily (although not exclusively) on in-house expertise, this could potentially limit the positive effects of PLCs on student achievement.

Having multiple perspectives at the table and a willingness to hear them builds the capacity of a PLC and helps teachers move beyond traditional beliefs and practices (Grossman et al., 2000). Without open and honest conversations about these beliefs, practices, and disagreements, the result is a "pseudocommunity" and "the illusion of consensus" where people behave as if they all get along and agree (Grossman et al., 2000, p. 18). In this situation, the authors note, "there is no authentic sense of shared communal space but only individuals interacting with other individuals" (p. 19). PLCs can be hampered by the constraints of a work environment where certain ways of thinking are privileged and closed off to unconventional or innovative approaches (Burt, 2000; Giles & Hargreaves, 2006; Little, 1982).

Finally, research demonstrates that not all PLCs have the same shared values or orientation. For example, in his case studies of middle schools, Westheimer (1999) finds a continuum between what he calls "liberal" and "collective" communities. Liberal communities emphasize individual rights and autonomy among teachers, whereas collective communities emphasize teachers' membership in a community. While these different types of communities may all fall under the umbrella of PLCs, they represent very different philosophies and practices. One would not expect these two different types of communities to have the same effect on teaching practice and student achievement.

Knowledge Gaps in the Research on PLCs

As Vescio and her colleagues note, "At its core, the concept of a PLC rests on the premise of improving student learning by improving teaching practice" (2008, p. 82). While there is a great deal of descriptive research on PLCs, few studies have examined their impact on teachers' instructional practices, and fewer still have studied the impact on student achievement (Lomos et al., 2011; Stoll, 2006; Vescio et al., 2008). Given the limited number of quantitative empirical studies on the topic, and the generally positive results that have emerged from studies that have been conducted, there is still much work to be done in this area.

Qualitative research like Little's (1982) ethnography of six urban schools has suggested a positive impact of PLC-type activities on student achievement. In this study, Little explored the social organization of schools and its relationship to school-level standardized test scores in reading, language arts, and math. She found that the more successful schools in her sample provided teachers with greater opportunities to collaborate. Little also found evidence of within-school differences where departments whose teachers met more often to discuss teaching practice and the curriculum reported improved student performance greater than other departments.

Little identified four types of collaborative practices as particularly critical to school success: "specific support for discussion of classroom practice, mutual observation and critique, shared efforts to design and prepare curriculum, and shared participation in the business of instruction improvement" (1982, p. 332). Teachers in the more successful schools frequently talked with one another about teaching practice. They discussed, developed, and assessed instructional materials together; they were observed teaching and received constructive criticism about their instructional practice; and they learned from one another (Little, 1982). These practices foreshadow the essential elements described by Louis and Marks: promoting shared values, reflective dialogue, deprivatization of practice, collaboration, and a focus on student learning (1996). Little's work informed later research in terms of identifying the types of collaborative activities that appear most important in influencing teacher and student outcomes. The study, however, only examined six schools and did not statistically account for other student- and school-level characteristics that have been shown to affect teacher and student outcomes.

Focusing specifically on collaboration, a key element of PLCs, Goddard, Goddard, and Tschannen-Moran (2007) conducted a survey of 452 fourth-grade teachers in 47 elementary schools in an urban school district. Goddard et al. used HLM to analyze teacher collaboration and its relationship to reading and math scale scores of 2,536 fourth-grade students. Teacher collaboration was measured by the extent to which teachers worked together on school improvement planning, choosing instructional methods, evaluating curricula, determining professional development needs and goals, and planning professional development activities. After controlling for characteristics such as students' gender, race/ethnicity, FRPL status, and prior achievement, the authors found that schoolwide teacher collaboration had a moderately significant positive relationship to student achievement in both math and reading at the .10 level (2007).

More recently, Ronfeldt, Farmer, McQueen, and Grissom analyzed the relationship between teacher collaboration and student achievement in Miami-Dade Public Schools using survey, administrative, and value-added data (2015). They found that teacher collaboration showed significant and positive effects on school-level and teacher-level reading and mathematics value-added test scores (Ronfeldt et al., 2015). Schools and teachers engaged in higher-quality collaborative activities showed high achievement gains in math and reading than those who were not engaged in these activities. While these studies examined student achievement statistically, they are not national studies and focused only on collaboration. In addition, the study by Goddard et al. did not link teacher data to individual students or classrooms.

In a large, quantitative study that looked at "communally-organized schools," Lee, Smith, and Croninger (1997) analyzed data from more than 9,500 secondary students in nearly 800 schools. Controlling for student- and school-level characteristics, the researchers found that in schools organized like PLCs, teachers had worked together and changed their classroom pedagogy more so than in bureaucratically-organized schools (Lee et al., 1997). Specifically, the authors found that teachers in communally-organized schools incorporated more higher-order instructional strategies. Students in these schools demonstrated larger gains in math, science, history, and reading achievement than students in schools where teachers' work was organized in more traditional, bureaucratic ways. While this study analyzed data from students and schools across the nation, the goal of the study was to examine the extent to which various features of academic and social organization are associated with higher student achievement. PLCs were not the primary focus of the study and as a result, measures of PLCs included in the analysis were limited. The study also did not investigate whether differential effects of PLCs exist by student and school characteristics.

In addition to individual studies such as these, some researchers have reviewed the literature on PLCs and assessed the reported effects on student achievement. First, Vescio et al.

(2008) conducted a review of 11 studies that examined the impact of PLCs on teacher instruction, eight of which also examined the impact on student achievement. They found that across the reviewed research, PLCs showed a positive impact on both teachers' instructional approach and student achievement (2008). More recently, Lomos and her colleagues (2011) conducted a meta-analysis of five studies that focus on the impact of PLCs in secondary schools. Like Vescio and her colleagues, Lomos et al. found a small but positive significant impact on student achievement, although they note that this is due primarily to a study by Lee and Smith (1996) on collective responsibility.

The Lee and Smith study included in the review by Lomos et. al. focused on three constructs measuring the organization of teachers' work—collective responsibility, staff cooperation, and control over classroom and school conditions (1996). These constructs share some similarities to those described by Louis and Marks (1996): a focus on student achievement (collective responsibility) and collaboration (cooperation). The authors found that achievement gains were higher in schools with higher levels of collective responsibility and cooperation. They also found that achievement gains were more equitably distributed in schools with higher levels of collective responsibility. Lee and Smith implemented a strong study design, employing similar methods to those used in this study (e.g., factor analysis and HLM). The current study differs from Lee and Smith's work in its operationalization of PLCs, its focus on elementary schools, and the inclusion of composite measures of PLCs in the analysis rather than examining each element separately (e.g., cooperation among teachers). In addition, like Lee et al., Lee and Smith did not investigate whether differential effects of PLCs existed.

The current study is not the first study to use ECLS-K data to examine the effect of PLCs on student gains in reading and mathematics. In a study by Burdett (2009), the dimensions of

PLCs were defined as “shared and supportive leadership, shared values and vision, collective learning and application, shared personal practice, and supportive conditions,” a somewhat different conceptualization than what is used in this study (p. 10). Burdett used 14 items from the teacher questionnaire related to these elements and examined their effect on student achievement separately and as part of two broader PLC constructs—support and collaboration—based on results from PCA. The questionnaire items used by the current study mostly overlap with those used by Burdett, but there are key differences (e.g., Burdett included an item on parent support, which this study did not). Burdett found individual PLC items and the support and collaboration constructs had significant effects on student achievement, but key student-, teacher-, and organizational-level variables were not controlled for in his analysis, the incusion of which is a strength of the current study.

In an exploratory study that I conducted using ECLS-K data (Raue, 2009), I examined the effect of teachers’ collaborative practices on student performance in fifth-grade reading, and student- and school-level variables played an important role. For example, using an interaction term between collaboration and school-level SES, my analysis demonstrated that teacher collaboration had the weakest effect on schools with the lowest and highest levels of poverty. In schools at both ends of the poverty spectrum, the effect of teacher collaboration may have been outweighed by the presence or absence of other resources (e.g., technology, quality of instructional materials) and the level of skills and knowledge with which children enter school. These findings suggest that a robust examination of how individual-, teacher-, and school-level characteristics contribute to student learning is an important next step in the research on PLCs.

Study Significance

Given the breadth and depth of its national data collection, data from the ECLS-K provide a prime opportunity to study PLCs and their impact on students. The ECLS-K is a multi-source, multi-method longitudinal study comprising data about students, parents, teachers, and administrators across the United States and is designed to provide reliable data on a cohort of students and the multitude of factors that affect students' academic, social, emotional, and physical health-related outcomes (Tourangeau, Nord, Le, Sorongon, & Najarian, 2009). The sample comprises students from public and private schools, and diverse socioeconomic, racial, and ethnic backgrounds (Tourangeau et al., 2009). The study design provides researchers the ability to link student-level data to data on families, teachers, and schools on a vast array of topics including PLCs.

The findings from this study contribute to the field in several ways. First, the study addresses the need for more empirical evidence on the impact of PLCs on student performance using a large, national dataset. The research contributes to the growing knowledge base on whether PLCs positively impact student achievement. Previous research like the Goddard et al. study is often restricted to one district, so generalizability is limited, or data about teachers are not linked to individual students in their classroom. This study addresses both limitations.

Second, this study examines how PLCs affect various student populations differently, an area not previously addressed in the research. At the conclusion of his study, Burdett identified several areas for future research using the ECLS-K data, primarily by adding student-level characteristics that were not included in his HLM models. Previous research has demonstrated the powerful effect of student characteristics on their school achievement and the need to incorporate such characteristics in statistical models. This research examines how PLCs affect the reading and mathematics performance of 1) students of different socioeconomic statuses, 2) students of different races, and 3) students who are considered academically "at-risk."

In addition, this study looks beyond the PLC construct to provide a fuller examination of how a variety of organizational variables (e.g., school type and size, minority enrollment, and percentage of FRPL-eligible students) influence PLCs' effect on student performance. While the meta-analysis of PLCs' impact on student achievement found significant and positive effects, as did Burdett's study, Lomos et al. (2011) note that "the relatively small but clear effect of professional community may also be explained by the occurrence of possible mediators or facilitators within the educational effects model" (p. 140). Including these variables provides a more accurate indication of PLCs' role in student performance. Although there is research on how some organizational characteristics facilitate or impede PLCs and mediate their impact on student achievement, there is no clear consensus in terms of characteristics such as school size and type, and limited research on minority enrollment and school-level SES. This research provides valuable information about organizational characteristics that facilitate or limit the effect of PLCs.

Finally, there is a great deal of rhetoric emphasizing the importance of collaborative working environments for teachers and their benefits to students, including the U.S. Department of Education and the National Board for Professional Teaching Standards. As policymakers rethink policies that emphasize teacher performance evaluations and rewards and sanctions based on student achievement, there is a growing awareness that policies must also support teachers and schools in their educational efforts. Continued research on effective ways to provide that support is needed.

Conclusion

The teaching profession in the United States has been described as a lonely enterprise. Numerous researchers in the field of education have portrayed the physical, social, intellectual, and psychological isolation that characterizes teachers' work life, disconnected from their colleagues, both at the earliest stages of schooling in America up until the modern day. While some researchers have pointed to adaptive aspects of teacher isolation, there exists considerable empirical evidence of its negative consequences. For example, teacher isolation constrains professional learning and the dissemination of professional knowledge, increases teacher burnout, and lowers teacher retention. Importantly, the impact of isolation on teachers has consequences for students and their academic achievement, as well.

PLCs have been viewed by many in the education community as a remedy for teacher isolation. PLCs are seen as a mechanism that brings teachers together to learn from, share with, and support one another. PLCs capitalize on the resources already available within a school—the knowledge and experience of its staff. However, it has been noted that there is no clear definition of the concept or the necessary components that must be present for PLCs to have positive effects on teacher and student learning. Moreover, implementation of PLCs can be difficult as PLCs challenge professional norms of independence and autonomy. There is also little empirical quantitative data on the impacts of PLCs on student achievement, which is where this study contributes to the field.

CHAPTER 3

METHODOLOGY

Introduction

In this chapter, the methods and procedures of the study are described, beginning with a restatement of the purpose of the study and the research questions. The chapter continues with an overview of the data source for the study—the 1998-99 ECLS-K—and descriptions of the data and analytic samples. Next, the research design and data analysis procedures are explained.

Purpose of the Study

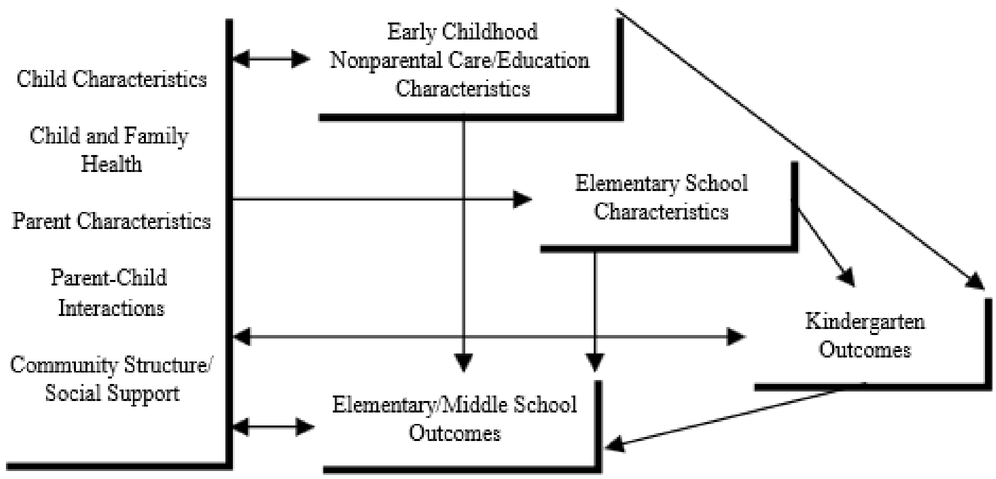
Using public-use data from the ECLS-K, the purpose of this study is to examine the effect of PLCs on students' performance in reading and mathematics and to investigate whether PLCs have differential effects on student performance based on student and school characteristics. Multilevel models are used to answer the study's research questions. The research questions are as follows:

1) What is the effect of PLCs on students' performance in reading and mathematics?
2) Do PLCs have differential effects on students' reading and mathematics performance based on the following student characteristics: SES, race, and at-risk status?
3) Do PLCs have differential effects on students' reading and mathematics performance based on the following school characteristics: school type, school size, minority enrollment, and percentage of students eligible for FRPL?

Overview of the ECLS-K

In 1998, NCES began following a nationally representative sample of kindergartners through the ECLS-K. The purpose of the study was to provide researchers, policymakers, and other stakeholders with a comprehensive set of reliable data on students' development from kindergarten through elementary and middle school (Tourangeau, Nord, Le, Sorongon, & Najarian, 2009). Data from the study provide a better understanding of "how various child, home, classroom, school, and community factors at various points in children's lives relate to cognitive, social, emotional, and physical development" (NCES, n.d.). The conceptual model for the ECLS-K is provided in Figure 3.1.

Figure 3.1. ECLS-K Conceptual Model



SOURCE: U.S. Department of Education, National Center for Education Statistics, Early Childhood Longitudinal Study, Kindergarten Class of 1998–99 (ECLS-K), fall 1998.

The ECLS-K employed a multi-stage probability sampling design in which geographic areas consisting of counties or groups of counties were the primary sampling units (PSUs) (Tourangeau, Nord, Le, Pollack, & Atkins-Burnett, 2006). During the first stage of sampling, 100 PSUs were selected from a sampling frame of 1,335 PSUs. During the second stage of sampling, schools offering a kindergarten program were selected from the sampled PSUs. Private and public schools were sampled separately, with 914 public schools and 363 private schools selected. In the third and final stage of sampling, approximately 24 kindergarten students were selected from each of the sampled schools. In order to meet sample-size goals, private schools and Asian students were oversampled (Tourangeau, Nord, Le, Pollack, & Atkins-Burnett, 2006). The base-year sample is nationally representative of the 3.8 million children who were enrolled in kindergarten in the 1998–1999 school year (Tourangeau et al., 2006, p. 1-1). Table 3.1 provides the number of unweighted sample sizes for each of the seven periods of data collection.

Table 3.1. Year and Unweighted Sample Sizes for Data Collection Periods

Data Collection Period	Date	Unweighted Sample Size
Fall Kindergarten	Fall 1998	21,387
Spring Kindergarten	Spring 1999	22,813
Fall First Grade	Fall 1999	6,507
Spring First Grade	Spring 2000	21,357
Spring Third Grade	Spring 2002	21,357
Spring Fifth Grade	Spring 2004	16,143
Spring Eighth Grade	Spring 2007	12,129

Adapted from Tourangeau, K., Nord, C., Le, T., Sorongon, A.G., & Najarian, M. (2009). Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K): Combined user's manual for the ECLS-K eighth-grade and K-8 full sample data files and electronic codebooks (NCES 2009-004). Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Data Collection Instruments

The ECLS-K is a multi-source, multi-method longitudinal study that collected data from students, parents, teachers, and administrators across the United States (Tourangeau, Nord, Le, Sorongon, & Najarian, 2009). The study spanned seven data collection periods between 1998 and 2007: fall and spring of kindergarten (1998 and 1999), fall and spring of first grade[1] (1999 and 2000), spring of third grade (2002), spring of fifth grade (2004), and spring of eighth grade (2007). The comprehensive set of data collection instruments included direct child assessments with cognitive, physical, psychomotor, and socioemotional development components; parent

[1] The first-grade fall data collection was administered to a subset of students sampled for the study.

interviews; teacher questionnaires; an administrator questionnaire; a school facilities checklist; and a student records abstract form (Tourangeau, Nord, Le, Sorongon, & Najarian, 2009). Descriptions of the data collection components used in this study are provided in Table 3.2 and are drawn from the ECLS-K user's manuals (Tourangeau et al., 2006; Tourangeau et al., 2009) and psychometric reports (Najarian, Pollock, & Sorongon, 2009; Pollack, Najarian, Rock, & Atkins-Burnett, 2005). User manuals, reports, and instruments can be accessed on the study's website (NCES, n.d.). Modifications to the instruments occurred across data collection periods, many of which are noted below.

Table 3.2 Description of Data Collection Instruments

Instrument	Description	Administration
Direct Child Assessments	The cognitive component of the assessment was developed for the ECLS-K in consultation with experts in child development and elementary education. Psychometric instruments available at the time were reviewed and an item pool that reflected grade-appropriate test specifications was developed. The item pool was field tested to collect data on the developmental appropriateness of the items. The final assessment items were determined based on results from the field test and covered the following subject areas: reading, mathematics, general knowledge (kindergarten and first grades), and science (third, fifth, and eighth grades). Assessments were designed to provide an indicator of students' academic ability in each of the subject areas at a given point in time and to determine growth of students' skills over time.	A language screener was administered to students whose primary home language was not English as determined by school records or students' teachers to determine if students understood English well enough to take the direct child assessment in English. Students who met an established cut score on the screener were administered the assessment in English in its entirety. Students who did not meet the cut score and whose home language was Spanish were administered an abbreviated version of the assessment in Spanish. Students who did not meet the cut score and whose home language was not Spanish had only their height and weight measured. The screener was administered in subsequent data collection periods to students who had not previously met the cut score in order to reevaluate their ability to take the direct child assessment in English. Trained assessors administered one-on-one, untimed assessments and entered students' answers into a laptop computer in the first six periods of data collection. In round seven, assessors administered timed assessments to groups of sampled students in the

Table 3.2 Description of Data Collection Instruments—Continued

Instrument	Description	Administration
		same school. Each subject matter assessment consisted of two sections: a short screener used to route students into a second section that varied in difficulty based on the number of questions students answered correctly during the previous section. The average length of the assessments varied, depending on grade level. For example, in the fall of kindergarten, assessments took approximately 50 to 70 minutes to administer and in fifth grade, assessments took approximately 96 minutes.
Parent Interviews	Interview content varied across data collection periods, but major topics included family structure, child care arrangements, student's health and well-being, social skills, and home environment; parent's background, education, employment, and income; parental involvement with the student's school; parental expectations for the student's education; and neighborhood information.	Computer-assisted parent interviews were conducted to provide important information about students and their home life. Interviews were conducted with a parent, guardian, or adult, most commonly the students mother, as long as the respondent was at least 18-years-old, living in the same household as the student, and knowledgeable about the student's care and education. Interviews were conducted primarily in English, but translated protocols were available to interview parents in other languages. Parent interviews were conducted primarily by phone and ranged from an average of 35 minutes in fall of first grade to 65 minutes in spring of kindergarten.

Table 3.2 Description of Data Collection Instruments—Continued

Instrument	Description	Administration
Teacher Questionnaires	Content varied across data collection periods, but major topics included a description of the teacher's class (e.g. demographics); class organization; classroom characteristics; instructional information; parental involvement; professional development; evaluation and grading practices; views on school readiness, school climate, and influence on school policies; and the teacher's demographic and background information.	In the first five periods of data collection, teachers who taught students for the majority of the day completed self-administered, paper-and-pencil questionnaires. In periods six and seven (i.e., spring of fifth and eighth grades), the administration of teacher questionnaires changed to reflect the greater likelihood that students have different teachers for different subjects once they enter middle school: all students were assigned to have their reading teacher complete the questionnaire and were randomly assigned to have either their mathematics or science teacher complete the questionnaires. If a student had the same teacher for all three subjects, his or her teacher was asked to complete a reading questionnaire and either a mathematics or science questionnaire, depending on the student's random assignment.
Administrator Questionnaire	The questionnaire collected information about the school, its student body and teaching staff, and information about principals' background and assessment of school climate.	Administrators completed a self-administered, paper-and-pencil questionnaire.

Variables

This study uses data from the cognitive component of the direct child assessments, the parent interviews, the teacher questionnaires, and the administrator questionnaires. The variables used in the analysis are described below and in Table 3.3.

IRT Scale Scores in Reading and Mathematics.[2] Several measures of students' performance on the cognitive component of the direct child assessments were computed for the ECLS-K. This study uses item response theory (IRT) scale scores in reading and mathematics. IRT scale scores are single, criterion-referenced measures of performance and can be used in longitudinal studies to measure growth with the caveat that gains made at different points along the continuum are qualitatively different (Tourangeau et al., 2006, p. 3–23). IRT scale scores are an estimate of the scores students would have received had they answered all the questions in the assessment (Tourangeau et al., 2006). IRT uses "the pattern of right, wrong, and omitted responses to the items actually administered in an assessment and the difficulty, discriminating ability, and 'guess-ability' of each item to place each student on a continuous ability scale" (Tourangeau et al., 2006, p. 3–6).

Time. This variable indicates data collection period: fall of kindergarten, spring of kindergarten, spring of first grade, fall of third grade, and fall of fifth grade.

Student Gender. This composite variable is derived from the parent interview, child report, and the Field Management System (FMS).[3] If information on a student's gender was missing in the most recent data collection period, data from a previous data collection period was

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[2] See chapter 7 in the "Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K): Combined user's manual for the ECLS-K eighth-grade and K-8 full sample data files and electronic codebooks" for more information about this or any of the variables used in the ECLS-K. Readers can also refer to the "Early childhood longitudinal study, kindergarten class of 1998–99 (ECLS-K): Psychometric report for the eighth grade" for more information about the IRT scale scores and how they were developed.

[3] The FMS was used throughout the study to enter data on sampled children, parents, teachers, and schools and to monitor data collection activities (Tourangeau et. al, 2009).

used. If there were discrepancies across data collection periods, the most frequently reported gender was used.

Student Race/Ethnicity. Data on students' race was obtained from the parent interview or the FMS if parent interview data were not available. The race/ethnicity variable was originally coded into eight categories: White, non-Hispanic; Black or African American, non-Hispanic; Hispanic, race specified; Hispanic, no race specified; Asian; Native Hawaiian or other Pacific Islander; American Indian or Alaska Native; and more than one race specified, non-Hispanic. The current study recoded the race/ethnicity variable into a dichotomous variable: White and Asian comprises one category, and Black or African American, Hispanic, Native Hawaiian or other Pacific Islander, American Indian or Alaska Native, and multiracial comprises a second category.

Student SES. Using data from the parent interview, the ECLS-K study created a composite variable for SES that is an average of up to five measures: father's (or male guardian's) education and occupation, mother's (or female guardian's) education and occupation, and household income. Individual measures were standardized to have a mean of 0 and a standard deviation of 1. The SES variable used in this study is a continuous variable.

Student At-Risk Status. Two dummy variables were created indicating whether a student is academically at risk in reading or mathematics. For each subject, students with IRT scale scores in the bottom quartile of student performance in at least 50 percent of the data collection periods for which they had a score available are considered at-risk.

Teacher Highest Degree. This dummy variable indicates whether a teacher attained a degree above a Bachelor's degree.

Teacher Job Satisfaction. This variable is an average of three items from the teacher questionnaire: the extent to which teachers agreed that they 1) really enjoy their present teaching job, 2) are certain that they are making a difference in the lives of the children they teach, and 3) would choose teaching again as their career if they could start over.

Professional Learning Community: Teacher Collaboration. This variable is a composite of four items from the teacher questionnaire that reflect discussion and collaboration among teachers: how frequently teachers met with other teachers to discuss 1) lesson planning, 2) curriculum development, 3) individual children, and 4) children with disabilities. PLC variables were created for this study using PCA, which is discussed in more detail later in this chapter.

Professional Learning Community: School Climate. This variable is a composite of nine items from the teacher questionnaire pertaining to a school climate indicative of professional learning communities. Five of the nine items reflect school climate more generally: how much teachers agreed that 1) staff members in the school generally have school spirit; 2) teachers feel accepted and respected as a colleague by most staff members; 3) teachers in this school are continually learning and seeking new ideas; 4) there is broad agreement among the entire school faculty about the central mission of the school; 5) how much influence teachers think they have over school policy in areas such as determining discipline policy, deciding how some school funds will be spent, and assigning children to classes. Four of the nine items reflect supportive leadership: how much teachers agreed that the school administrator 1) knows what kind of school he/she wants and has communicated it to the staff; 2) deals effectively with pressures from outside the school that might otherwise affect teaching; 3) sets priorities, makes plans, and sees that they are carried out; and 4) is supportive and encouraging.

School Type. This composite variable codes school type into two categories: public and private. Data were collected from the school administrator questionnaire. The public-school category includes public comprehensive schools, magnet schools, and schools of choice. The private school category includes religious schools and other private schools.

School Size. This composite variable indicates total school enrollment primarily based on data from the school administrator questionnaire. Data from the Private School Universe Survey (PSS) and the Common Core of Data were used when data from the administrator questionnaire were missing. In the public use dataset, total school enrollment data were coded into five categories: 0 – 149 students, 150 – 299 students, 300 – 499 students, 500 – 749 students, and 750 or more students. After kindergarten, only a small percentage of students fell into the first category. For this study, school enrollment data were recoded into three categories: 0 – 299 students, 300 – 749 students, and 750 or more students.

Minority Enrollment. This composite variable indicates the percentage of minority students in a school. Data were collected from the school administrator questionnaire and the percentage is based on the sum of percentages for all categories except White, non-Hispanic. In the public use dataset, this variable is coded into five categories: less than 10 percent minority enrollment, 10 to less than 25 percent, 25 to less than 50 percent, 50 to less than 75 percent, and 75 percent or more. For this study, minority enrollment has been recoded into three categories: less than 25 percent, 25 to less than 75 percent, and 75 percent or more.

Free and Reduced Price Lunch. This is a continuous, composite variable that indicates the percentage of students eligible for FRPL enrolled in a school. Data were collected from the school administrator questionnaire and missing data were imputed.

Table 3.3. Description of Variables

Variable	Values
Outcome Variables	
Item Response Theory (IRT) Scale Scores in Reading and Mathematics	Reading = 21.07 – 203.22, 84.85 (mean), 49.01 (SD); Mathematics = 10.51 – 170.66, 64.92 (mean), 39.50 (SD)
Data Collection Period Variable	
Time	0 = Fall kindergarten 1 = Spring kindergarten 2 = Spring first grade 3 = Spring third grade 4 = Spring fifth grade
Student-Level Variables	
Student Gender	1 = Male 0 = Female
Student Race/Ethnicity	1 = Black or African American, Hispanic, Native Hawaiian or other Pacific Islander, American Indian or Alaska Native, and multiracial 0 = White or Asian
Student Socioeconomic Status (SES)	-2.62 to 2.66
Student At-Risk Status	1 = Academically at risk 0 = Not academically at risk
Teacher- and School-Level Variables	
Teacher Highest Degree	1 = Advanced degree 0 = No advanced degree
Average Teacher Job Satisfaction	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree
Professional Leaning Community: Teacher Collaboration	1 = Never 2 = Once a month or less 3 = Two or three times a month 4 = Once or twice a week 5 = Three or four times a week 6 = Daily
Professional Learning Community: School Climate	1 = Strongly disagree 2 = Disagree 3 = Neither agree nor disagree 4 = Agree 5 = Strongly agree

Table 3.3. Description of Variables—Continued

Variable	Values
Teacher- and School-Level Variables	
School Type	1 = Private 0 = Public
School Size – Small	1 = 0 – 299 students 0 = 300 or more students
School Size – Medium	1 = 300 – 749 students 0 = 0 – 299 and 750 or more students
School Size – Large	1 = 750 or more students 0 = Less than 750 students
Minority Enrollment – Low	1 = 0 to less than 25 percent minority enrollment 0 = 25 percent or more minority enrollment
Minority Enrollment – Medium	1 = 25 to less than 75 percent minority enrollment 0 = Less than 25 percent and more than 75 percent enrollment
Minority Enrollment – High	1 = 75 percent or more minority enrollment 0 = 0 to less than 75 percent minority enrollment
FRPL Eligibility	0 to 100 percent

Strengths and Limitations of the ECLS-K Dataset

The ECLS-K is a valuable dataset for the current study for several reasons. The data are nationally representative of the 1998–1999 cohort of kindergartners allowing for the generalizability of the findings. The data are also longitudinal in nature, representing more than a single snapshot in time. The scope of data sources and topics covered are also comprehensive. In addition to several PLC-related items, the ECLS-K collected data on numerous student-, teacher-, and school-level factors that have been shown to influence student achievement and are therefore important to include in the analysis to better understand PLCs' effect on achievement after accounting for these other factors.

However, generalizability is limited in several ways. After data collection in the spring of first grade, the study sample was no longer "freshened" to include children who did not have an opportunity to participate in the study during kindergarten or first grade (e.g., recent immigrants who enrolled in U.S. schools after the 1999–2000 school year) (Tourangeau et al., 2006). Consequently, the third-, fifth-, and eighth-grade samples do not represent all third-, fifth-, and eighth-grade students. Rather, these samples represent the cohort of students who entered kindergarten in the U.S. in 1998 or first grade in 1999, which is an estimated 96 percent of third graders during the 2001–2002 school year, 83 percent of fifth graders during the 2003–2004 school year, and 80 percent of eighth graders during the 2006–2007 school year (Tourangeau et al., 2009, p. 4-29).

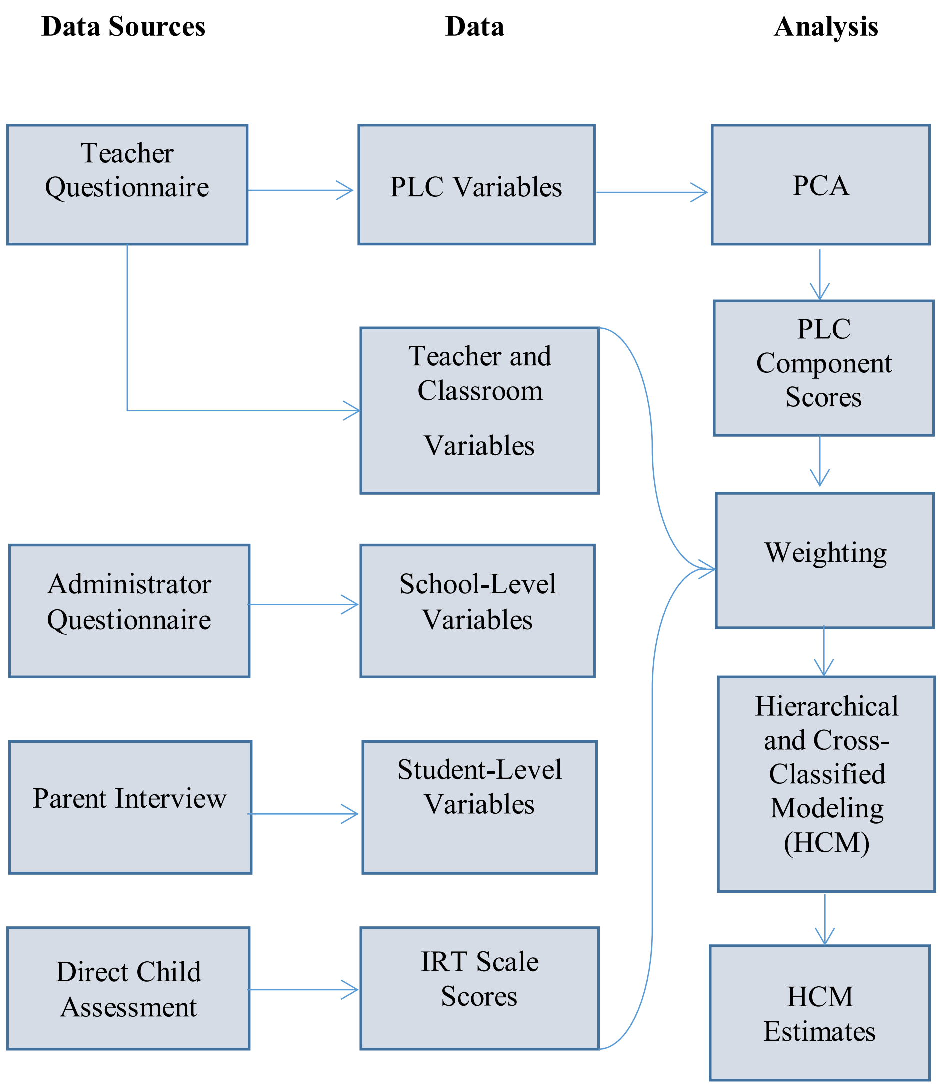
Moreover, the ECLS-K followed students, so teachers and schools were only sampled in later grades if they included one or more ECLS-K student in their classrooms (NCES, 2009). Therefore, the study is not representative of teachers or schools. This study also excluded from the analysis students who changed schools during the study. If students who changed schools differed from their peers in meaningful ways, bias may have been introduced into the sample. A comparison between the full and analytic samples later in this chapter suggests that the samples were significantly different with respect to reading performance.

Finally, because the ECLS-K was not specifically focused on PLCs, the teacher questionnaires were not designed to capture a full range of data on teachers' participation in learning communities, and no PLC variables were included on the eighth-grade questionnaires. As a result, the PLC constructs are not as robust as they might be otherwise.

Statistical Methods

This study used PCA to examine the correlations among select items in the teacher questionnaire and create PLC variables. HCM was then used to analyze the impact of student-, teacher-, and organizational-level variables on students' reading and mathematics performance. Each method, including the selection and use of weights, is described in further detail below. A process chart of the data sources, data, and analysis is presented in Figure 3.2.

Figure 3.2. Process Chart of Data Sources, Data, and Analysis



Weights

As noted earlier in this chapter, the ECLS-K followed a nationally representative sample of kindergartners. In collecting such data, the study employed a multistage, stratified, clustered design within primary sampling units (PSUs) to reduce data collection costs (Tourangeau et al., 2006). It also involved oversampling private schools and Asian and Pacific Islander children to ensure they were sufficiently represented in the sample (Tourangeau et al., 2006). This type of complex sampling poses challenges for data analysis. For example, unlike simple random sampling, complex sampling creates a situation where the probability of selecting a particular unit (e.g., a student) may vary depending on factors such as the size or location of the unit. Most statistical tests, however, assume that the data being analyzed are based on a simple random sample in which each study participant has an equal chance of being selected for inclusion in the sample (Hahs-Vaughn, 2005; NCES, 2009).

Ignoring the sampling design and using a simple random sampling approach in analysis leads to biased estimates. Standard errors, which measure "the precision of estimates and the statistical significance of hypothesis tests," would be underestimated (Davern & Strief, 2008, p. 1). This increases the risk that nonsignificant results would present themselves as significant (Hahs-Vaughn, 2005; NCES, 2009). For example, in this study, the PLC constructs might appear to have statistically significant effects on students' reading or mathematics performance when, in fact, they do not. Similarly, other variables in the analysis might also inaccurately appear to have a statistically significant effect. To overcome such challenges, the analysis of nonrandom samples typically involves the application of weights (Hahs-Vaughn, 2005; NCES, 2009). In the ECLS-K, multiple weights are provided for researchers to account for the differential selection probabilities and differential patterns of response and nonresponses (Tourangeau et al., 2006).

Appropriate weights are selected based on the level of analysis (e.g., student level), the source(s) of the data (e.g., direct child assessments, teacher questionnaires), and the data collection period(s) of data used. Although a "perfect" weight may not exist for the type of analysis being conducted, using an inappropriate weight would introduce bias into the estimates because appropriate weights "account for differential probabilities of selection at each sampling stage and to adjust for the effects of nonresponse" (Tourangeau et al., 2006, p. 4–28). Using an inappropriate weight could therefore result in systematically under- or overestimating the population parameter. For example, results would be biased because of oversampled populations.

There are two primary ways of weighting data to account for the complexity of the sample design in the analysis: exact and approximation methods. The exact method extracts replication weights included in the dataset and runs an analysis based on those weights (Hahs-Vaughn, 2005; NCES, 2009). The approximation method used in this study is a less ideal, but acceptable way to handle data from complex, nonrandom samples. Using the approximation method, raw weights are normalized so that the standard error is based on the sample size as opposed to the population size (Hahs-Vaughn, 2005; NCES, 2009). A design effect (DEFF) is then applied to account for the complex sampling design (Hahs-Vaughn, 2005; NCES, 2009). The DEFF is the ratio of variance of a statistic based on complex sampling considerations to the variance of the statistic for a simple random sample (Hahs-Vaughn, 2005).

Using the approximation method, the first step is to normalize the raw weight. The normalized weight is obtained by dividing the sample size by the population size and then multiplying the quotient by the raw weight. In this study, the ECLS-K weight C1_6FP0 is used. The ECLS-K User's Manual recommends C1_6FP0 when analyzing "parent interview data from FIVE rounds of data collections involving the FULL sample of children (fall-kindergarten, spring-kindergarten, spring-first grade, spring-third grade, spring-fifth grade), alone or in conjunction with any of the child assessment, school, teacher, or classroom data" (2006, p. 9–5). The normalized weight is then divided by the DEFF for the outcome variables—in this case, reading and mathematics IRT scale scores—to create an adjusted weight (Hahs-Vaughn, 2005).

Normalized weight = (ECLS-K weight) * (sample n/population N)
Adjusted weight = normalized weight/DEFF of outcome variable

Analytic Samples

This study used data from the eighth-grade public use file of the ECLS-K, which contains the complete set of data from all data collection periods. This study is limited to an examination of data from the fall of kindergarten through the spring of fifth grade due to the omission of the PLC items from the teacher questionnaires in the eighth-grade data collection period. The analytic samples are restricted to data from students while they remained in the school from which they were initially sampled. For example, if a student changed schools in third grade, data from kindergarten and first grade were used in the analysis. Fifth-grade students who were randomly assigned to have their science teacher as opposed to their mathematics teacher complete a questionnaire were also excluded from the mathematics analysis because their math teacher did not complete a questionnaire.

Missing Data

There are two types of missing data that are of concern for this study: unit nonresponse and item nonresponse. Unit nonresponse occurs when a sampled unit (e.g., a student or teacher) does not participate in the study and there are no data for that sampled unit in the analysis (Yan & Curtin, 2010). One way to address bias resulting from unit nonresponse is to apply weights to the data so that the sample better reflects the population. Item nonresponse occurs when a sampled unit participates in the study but has incomplete data (Yan & Curtin, 2010). The ECLS-

K imputed some missing data, for example, by using available data from earlier data collection periods to complete cases from later data collection periods. In this study, these two types of missing data are essentially treated the same because HCM excludes cases with any missing data. If the students excluded from the analysis do not differ in meaningful ways from the population, the sample remains representative of the overall population. If that is not the case, then the analysis presented here is biased.

As noted in table 3.1, the ECLS-K began with 21,387 students in the fall of kindergarten. By the spring of fifth grade, the last year of data used in this study, 16,143 students were participating in the ECLS-K. For this study, the unweighted number of students in reading is 7,973 and the unweighted number of students in mathematics is 8,042—in both cases, 49 percent of the fifth-grade sample and 37 percent of the fall kindergarten sample.

T-test comparisons were used to investigate bias resulting from differences between the analytic samples and the full sample that might limit the study's generalizability. No attempt was made to address missing data beyond applying the appropriate weights and benefiting from the imputation done as part of the ECLS-K. Table 3.4 presents selected characteristics for the full ECLS-K sample and the analytic samples. The results from the t-tests show that the analytic samples do not differ significantly from the full samples on students' gender, race, SES, or at-risk status. However, the reading analytic sample does differ significantly from the full sample when comparing students' IRT scale scores. In the analytic sample, students' reading performance is significantly higher than those in the full sample and indicates bias in the reading sample.

Table 3.4. Comparison of the Weighted Mean Estimates for the Full and Analytic Samples

Student Characteristics	Full Sample		Reading Analytic Sample		Full vs. Analytic Sample T Statistic	Mathematics Analytic Sample		Full vs. Analytic Sample T Statistic
	Mean	SD	Mean	SD		Mean	SD	
Gender								
Male	.5146	.49988	.5144	.49993	0.013	.5142	.50003	0.022
Race/Ethnicity								
White, Non-Hispanic	.5767	.49418	.5774	.49411	-0.046	.5765	.49435	0.011
Black, non-Hispanic	.1597	.36643	.1602	.36686	-0.044	.1599	.36672	-0.015
Hispanic	.1886	.39123	.1872	.39021	0.116	.1885	.39127	0.007
Asian	.0267	.16137	.0267	.16133	0.000	.0267	.16125	0.000
Other, non-Hispanic	.0483	.21443	.0485	.21484	-0.030	.0484	.21474	-0.013
Socioeconomic Status (SES)	-.0740	.75129	-.0728	.75089	-0.052	-.0742	.75138	0.007
At-Risk Status	.2617	.43966	.2617	.43966	0.000	.2467	.43129	0.948
Reading IRT Scale Score	79.85	47.52	84.85	49.01	-3.357*	-		-
Mathematics IRT Scale Score	62.41	39.40	-		-	64.92	39.50	-1.743

Note. An asterisk indicates a significant difference.

PCA

PCA is closely related to factor analysis, which broadly covers a variety of statistical techniques used to analyze the existence of underlying, unobserved constructs as represented by observed variables and the relationships among them (Kim & Mueller, 1978). These techniques are used to simplify interrelated measures, which is recommended for purposes of parsimony and error reduction and can help build and confirm theory (Child, 1990; Thompson, 2004). However, all these techniques involve some degree of subjectivity, and more than one interpretation can reasonably be drawn from the analysis (e.g., the number of factors to use).

PCA is data-driven; a researcher does not need to have a specific theory about underlying constructs to conduct the analysis (Thompson, 2004). Alternatively, Confirmatory Factor Analysis (CFA) is theory-driven and allows a researcher to use theoretical and/or empirical knowledge to test hypothesized relationships between the observed variables and latent constructs (Suhr, 2006). This study relies on PCA to examine several variables from the teacher questionnaire and identify PLC variables for inclusion in the HCM analysis. CFA was also used to examine these variables; the results are reported in Appendix B.

PCA in this study was conducted with SPSS 24 using unweighted teacher-level data. Teachers who did not respond to at least half of the PLC-related questionnaire items were excluded from the analysis. Seventeen variables from the teacher questionnaire were initially hypothesized as correlated. These variables are described in Table 3.5.

Table 3.5. Initial PLC Variables Included in PCA[a]

ECLS-K Variable Name	Questionnaire Item	Scale
COMMTE	To what extent do you integrate curriculum areas around common or unifying themes (e.g., using math and science concepts in the same unit of study or using arts and social studies in the same unit of study)?	1 – 4: never, occasionally, usually, always
	How often have you participated in the following school-related activities since the beginning of the school year?	1 – 6: never, once a month or less, two or three times a month, once or twice a week, three or four times a week, daily
LESPLN	Meeting with other teachers to discuss lesson planning?	
CURRDV	Meeting with other teachers to discuss curriculum development?	
INDCHD	Meeting with other teachers or specialists to discuss individual children?	
DISCHD	Meeting with the special education teacher or service providers to discuss and plan for the children with disabilities in my class?	
	Please indicate the extent to which you agree with each of the following statements about your school's climate.	1 – 5 scale: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree
SCHSPR	Staff members in this school generally have school spirit.	
NOTCAP	Many of the children I teach are not capable of learning the material I am supposed to teach them. (reverse coded)	
ACCPTD	I feel accepted and respected as a colleague by most staff members.	
CNTNLR	Teachers in this school are continually learning and seeking new ideas.	

Table 3.5. Initial PLC Variables Included in PCA—Continued

ECLS-K Variable Name	Questionnaire Item	Scale
SCHPLC	At your school, how much influence do you think teachers have over school policy in areas such as determining discipline policy, deciding how some school funds will be spent, and assigning children to classes?	1 – 5 scale: no influence, slight influence, some influence, moderate influence, a great deal of influence
CNTRLC	How much control do you feel you have IN YOUR CLASSROOM over such areas as selecting skills to be taught, deciding about teaching techniques, and disciplining children?	1 – 5 scale: no influence, slight influence, some influence, moderate influence, a great deal of influence
	Please indicate the extent to which you agree with each of the following statements about your school's environment.	1 – 5; strongly disagree, disagree, neither agree nor disagree, agree, strongly agree
STNDLO	The academic standards at this school are too low. (reverse coded)	
MISSIO	There is broad agreement among the entire school faculty about the central mission of the school.	
ALLKNO	The school administrator knows what kind of school he/she wants and has communicated it to the staff.	
PRESSU	The school administrator deals effectively with pressures from outside the school (for example, budget, parents, school board) that might otherwise affect my teaching.	
PRIORI	The school administrator sets priorities, makes plans, and sees that they are carried out.	
ENCOUR	The school administration's behavior toward the staff is supportive and encouraging.	

[a] Several PLC-related questionnaire items measure teachers' perceptions of school-level characteristics and may not accurately reflect the school climate

As a first step, PCA was used to extract components with eigenvalues greater than one (i.e., the Guttman-Kaiser rule). Eigenvalues represent the total variance explained by each component. The suitability of the data for PCA was tested using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity.

Because the Guttman-Kaiser rule tends to overestimate the number of components that are present in the data, a scree plot of the components was also examined (Cliff, 1988). Scree plots show the eigenvalues on the y axis and the number of components on the x axis. The point where the slope of the curve levels off gives an indication of the number of components that should be generated by the analysis. The number of components before the curve levels off are kept for analysis. Based on the scree plot generated for the 17 PLC variables, PCA was conducted two additional times, with two- and three-component limits set for extraction. Variables with component loadings less than .4 were then removed from the analysis.

Cross-Classified Random Effects Modeling (HCM)

HCM was used to answer the research questions by analyzing the relationship between PLCs on students' reading and mathematics performance and whether those relationships are moderated by student and school characteristics. The HCM analysis in this study relies on data from a variety of ECLS-K data: student performance in reading and mathematics from the direct child assessments, student-level data from the parent interview, teacher-level data from the teacher questionnaire, and school-level data from the administrator questionnaire. As noted previously, data were weighted to account for the complex sampling design of the ECLS-K.

Traditional HLM can handle hierarchical data structures where lower-level units are nested in higher-level units, which themselves may be nested in even higher-level units (Raudenbush & Bryk, 2002). In HLM, a lower-level unit can be nested in only one higher-level unit. For example, each student is a member of only one classroom and attends only one school. However, social relationships are often more complicated than this hierarchical structure allows. Due to the longitudinal nature of the data in this study, students were taught by multiple teachers during their elementary school years. In this case, students' scores on the reading and math direct assessments from kindergarten to fifth grade belong to a combination of students and teachers, which are nested in schools. As a result, HCM was used to account for students' mobility across grades. As noted earlier, the sample was restricted to data obtained from students while they remained in their original school.

Hong and Raudenbush (2008) used three-level HCM to investigate time-varying instructional treatments on student achievement. As in this study, they analyzed data from students who were moving across teachers who were nested within schools. Also, as in this study, repeated measures of student achievement were modeled at level 1, cross-classified by students and teachers at level 2, with teachers nested within schools at level 3 (Raudenbush, Bryk, Cheong, Congdon, & du Toit, 2011).

HCM is an appropriate analytical tool to answer the research questions because it can account for the naturally existing, nested structure of schools—students in the same classroom are expected to have outcomes more similar to one another than to students in other classrooms (Raudenbush & Bryk, 2002). The same can be said for students and teachers in different schools. HCM allows researchers to understand how each level of the nested structure impacts the outcome of interest—in this case, student performance on the ECLS-K reading and mathematics assessment. The advantages of using hierarchical models are well-documented (Raudenbush & Bryk, 2002; Hox, 2002). Compared with other analytical models, such as multiple regression and analysis of variance (ANOVA), HCM accurately models the hierarchical structure in the school setting, correcting for aggregation bias, misestimated precision, and the unit of analysis problem (Raudenbush & Bryk, 2002; Hox, 2002). Chaplin notes several limitations of HLM, which include its inability to account for negative within-group correlations in the error terms and the potential for biased estimates for models that use weights, which the models in this study do (2003). In addition, to run cross-classified models in HLM7 using weights, the sample had to be limited to students who did not change schools, limiting generalizability of the findings.

Levels of Analysis. Three levels of analysis were employed in this study. Time is the critical level 1 variable, which is cross-classified by students and teachers at level 2, with teachers nested within schools at level 3. This nested, hierarchical, and cross-classified structure represents teachers and students interacting over time. At level 1, students' reading and mathematics performance was modeled as a function of time between kindergarten and fifth grade. At level 2, performance was modeled as a function of student and school characteristics such as students' SES and school size. Finally, performance was modeled as a function of school type at level 3. The unconditional and fully conditional models are presented below.

Fully Unconditional Models. As a first step, a three-level unconditional model with no predictor variables was run separately for each outcome variable—reading and mathematics IRT scale scores. The unconditional model allows for the partitioning of the total variability in the outcome variable across levels of analysis (Garson, 2013). Level 1 represents within-time differences in reading and mathematics performance:

$$Y_{ijkl} = \pi_{0jkl} + e_{ijkl}$$

The outcome variable Y (i.e., the IRT scale score) at time i for child j with teacher k in school l is equal to the average outcome for child j with teacher k in school l plus the unique effect associated with time i for child j with teacher k in school j (error). Level 2 represents the within-school differences in performance:

$$\pi_{0jkl} = \theta_{0l} + b_{00jl} + c_{00kl}$$

At level 2, θ_{0l} is the average performance for school l plus the unique effects associated with student j and teacher k in school l (error). Level 3 represents the between-school differences in performance:

$$\theta_{0l} = \delta_{000} + d_{00l}$$

At level 3, δ_{000} is the average performance for all schools plus the unique effect associated with school l (error). The mixed model is:

$$Y_{ijkl} = \delta_{000} + b_{00jl} + c_{00kl} + d_{00l} + e_{ijkl}$$

Once the unconditional models are run for reading and mathematics, intraclass correlation (ICC) coefficients (i.e., the proportion of variance attributed to each level) can be calculated. Although it is assumed that multilevel analysis provides a better understanding of many phenomena in education because it takes into account the nested structure of these phenomena, calculating the ICC coefficients is a simple statistical method to determine whether the data warrant the use of a hierarchical model instead of a single-level method of analysis (Raudenbush & Bryk, 2002). ICC coefficients range from zero when there is no variability across groups (e.g., schools) to one when all the variability is across groups. The equations for calculating ICC coefficients at each level are as follows:

The proportion of variance at level 1 (i.e., the within-student variance) = $\sigma^2 / \sigma^2 + \tau_\pi + \tau_\beta + \tau_\gamma$

The proportion of variance at level 2 row (i.e., the between-student variance) = $\tau_\pi / \sigma^2 + \tau_\pi + \tau_\beta + \tau_\gamma$

The proportion of variance at level 2 column (i.e., the between-teacher variance) = $\tau_\beta / \sigma^2 + \tau_\pi + \tau_\beta + \tau_\gamma$

The proportion of variance at level 3 (i.e., the between-school variance) = $\tau_\gamma / \sigma^2 + \tau_\pi + \tau_\beta + \tau_\gamma$

Fully Conditional Models. While the fully unconditional models estimate the proportion of variance at each level of analysis, it is assumed that the part of the variability at each level can be explained by predictor variables at each level (Raudenbush & Bryk, 2002). Student, teacher, and school characteristics were added to the models to assess their effect on student performance in reading and mathematics. The fully conditional models answer the research questions regarding the effects of the PLC constructs identified during factor analysis on student performance while controlling for other variables that may also influence performance. The resulting fully conditional, mixed model for this study is:

$$IRTSCORE_{ijkl} = \delta_{000} + \delta_{001}*\text{SCTYP\_PR}_{kl} + \delta_{010}*\text{GENDER\_M}_{jl} + \delta_{020}*\text{AVESES}_{jl} + \delta_{030}*\text{ATRISK\_R}_{jl} + \delta_{040}*\text{RACE\_BHO}_{jl} + \delta_{050}*\text{PLC\_TC}_{jl} + \delta_{060}*\text{PLC\_SC}_{jl} + \delta_{070}*\text{AVESAT}_{jl} + \delta_{080}*\text{HGHSTD\_A}_{jl} + \delta_{090}*\text{ENRLS\_S}_{jl} + \delta_{0100}*\text{ENRLS\_L}_{jl} + \delta_{0110}*\text{MINOR3\_L}_{jl} + \delta_{0120}*\text{MINOR3\_H}_{jl} + \delta_{0130}*\text{FRPL\_M\_S}_{jl} + \delta_{100}*TIME\_R_{ijkl} + \delta_{101}*TIME\_R_{ijkl}*\text{SCTYP\_PR}_{kl} + \delta_{110}*TIME\_R_{ijkl}*\text{GENDER\_M}_{jl} + \delta_{120}*TIME\_R_{ijkl}*\text{AVESES}_{jl} + \delta_{130}*TIME\_R_{ijkl}*\text{ATRISK\_R}_{jl} + \delta_{140}*TIME\_R_{ijkl}*\text{RACE\_BHO}_{jl} + \delta_{150}*TIME\_R_{ijkl}*\text{PLC\_TC}_{jl} + \delta_{160}*TIME\_R_{ijkl}*\text{PLC\_SC}_{jl} + \delta_{170}*TIME\_R_{ijkl}*\text{AVESAT}_{jl} + \delta_{180}*TIME\_R_{ijkl}*\text{HGHSTD\_A}_{jl} + \delta_{190}*TIME\_R_{ijkl}*\text{ENRLS\_S}_{jl} + \delta_{1100}*TIME\_R_{ijkl}*\text{ENRLS\_L}_{jl} + \delta_{1110}*TIME\_R_{ijkl}*\text{MINOR3\_L}_{jl} + \delta_{1120}*TIME\_R_{ijkl}*\text{MINOR3\_H}_{jl} + \delta_{1130}*TIME\_R_{ijkl}*\text{FRPL\_M\_S}_{jl} + b_{10jl}*TIME\_R_{ijkl} + c_{10kl}*TIME\_R_{ijkl} + d_{10l}*TIME\_R_{ijkl} + e_{ijkl}$$

where

IRTSCORE_{ijkl} is the performance at time i of student j with teacher k in school l;

δ_{000} is the average performance when all predictor variables are set to zero;

δ_{001} is the level 3 intercept coefficient for teacher k in school l;

δ_{010} - δ_{040} are the level 2 row intercept coefficients for student j in school l;

δ_{050} - δ_{0140} are the level 2 column intercept coefficients for student j in school l;

δ_{100} is data collection period: 0 at fall of kindergarten, 1 at spring of kindergarten, 2 at spring of first grade, 3 at spring of third grade, and 4 at spring of fifth grade;

δ_{101} is the level 3 slope coefficient for teacher k in school l;

δ_{110} - δ_{140} are the level 2 row slope coefficients for student j in school l;

δ_{150} - δ_{1140} are the level 2 column intercept coefficients for student j in school l;

b_{00jl} is the unique effect associated with student j in school l (error);

c_{00kl} is the unique effect associated with teacher k in school l (error);

d_{00l} is the unique effect associated with school l (error);

e_{ijkl} is the unique effect associated with time i for student j with teacher k in school (error).

In all the conditional models, models specified a cumulative Z-structure, which allows effects to carry over from one data collection period to the next (Raudenbush et al., 2011). Continuous variables were centered on the grand mean. Several of the school-level variables were time variant and as a result, these variables were disaggregated to the teacher level. Specifically, school size, minority enrollment, and FRPL eligibility varied considerably across data collection periods and were therefore modeled at level 2.

Interactions Models. Interaction terms were added to the conditional models to answer research questions 2 and 3, which examine the moderating effects of student and school characteristics on the relationship between PLCs and student performance. Student-level variables included in the interaction term models were disaggregated at level 1 to conduct cross-level interactions with variables modeled at the teacher level.

CHAPTER 4

FINDINGS

Introduction

The purpose of this study is to examine the effect of PLCs on elementary school students' performance in reading and mathematics using data from the ECLS-K. This study also investigates whether professional learning communities have differential effects on student performance based on student and school characteristics. Specifically, the study answers the following research questions.

1) What is the effect of PLCs on students' performance in reading and mathematics?
2) Do PLCs have differential effects on students' reading and mathematics performance based on the following student characteristics: socioeconomic backgrounds, race, and at-risk status?
3) Do PLCs have differential effects on students' reading and mathematics performance based on the following school characteristics: school type, school size, minority enrollment, and percentage of students eligible for free and reduced price lunch?

The chapter begins with the results from the PCA, which lay the foundation for the next stage of analysis by helping to identify correlated PLC items in the ECLS-K teacher questionnaire. A summary of the findings from HCM follows the discussion on PCA. HCM was used to answer the research questions by analyzing the relationship between the PLC variables obtained from PCA and students' reading and mathematics performance and whether those relationships are moderated by student and school characteristics. The HCM analysis in this study relies on data from a variety of ECLS-K data: student performance in reading and mathematics from the direct child assessments computed as IRT scale scores, student-level data from the parent interview, teacher-level data from the teacher questionnaire, and school-level data from the administrator questionnaire. Data were weighted to account for the complex sampling design of the ECLS-K and to draw conclusions beyond the study respondents to the broader student population.

PCA

This study used PCA, a data-driven method, to explore underlying relationships among PLC items from the questionnaire (Thompson, 2004). CFA, a theory-driven method that tests hypothesized relationships (Suhr, 2006) was also used. The results of the CFA are reported in Appendix B.

PCA

Seventeen items from the teacher questionnaire that reflect key dimensions of PLCs were initially hypothesized as being correlated. The analysis was limited to teachers who had responded to at least half of the PLC-related questionnaire items being analyzed (i.e., 9 of the 17 items). The principal component method was used to extract components, and Promax rotation was used to account for any correlation between components.

The factorability of the 17 variables was examined using several accepted measures. First, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .857, well above the recommended value of .6 (Tabachnick & Fidell, 2001). Second, Bartlett's test of sphericity was significant ($\chi 2$ (136) = 79930.88, $p<.001$). Finally, the communalities, which indicate the amount of variance in each of the original variables explained by the extracted factors, were above .4 for all but one variable: STNDLO or the belief that the academic standards at a teacher's school were too low (.346). Given these measures, PCA was determined to be suitable for these variables.

The principal components method was then used to extract components with eigenvalues greater than one (i.e., the Guttman-Kaiser rule). Eigenvalues represent the total variance explained by each component. Five components with eigenvalues greater than 1 were identified. Because the Guttman-Kaiser rule tends to overestimate the number of components that are present in the data, a scree plot of the components was also examined (Cliff, 1988). The scree plot suggested that a two-component model, which explained 41 percent of the variance, or a three-component model, which explained 48 percent of the variance, was a better fit of the data than a five-component model (Exhibit 4.1). As a result, PCA was conducted two additional times, with two- and then three-component limits set for extraction.

When a two-component limit was set, communalities, which indicate the amount of variance in each of the original items explained by the extracted components, were low for seven items (less than .4). When a three-component limit was set, communalities for five of these items remained low (Table 4.1). These variables were COMMTE, the extent to which a teacher integrated curriculum areas around themes; NOTCAP, the belief that many of a teacher's students were not capable of learning; SCHPLC, the amount of influence over school policies teachers felt they had; CNTRLC, the amount of control over teaching and disciplinary strategies a teacher felt he or she had in his or her classroom; and STNDLO, the belief that the academic standards at a teacher's school were too low. NOTCAP and STNDLO were both negatively worded in the teacher questionnaire and therefore reverse coded prior to inclusion in the PCA so that higher values for all the questionnaire items indicated the same type of response (i.e., a higher value represents a more positive response).

Figure 4.1. Scree Plot of Components with Initial 17 Variables

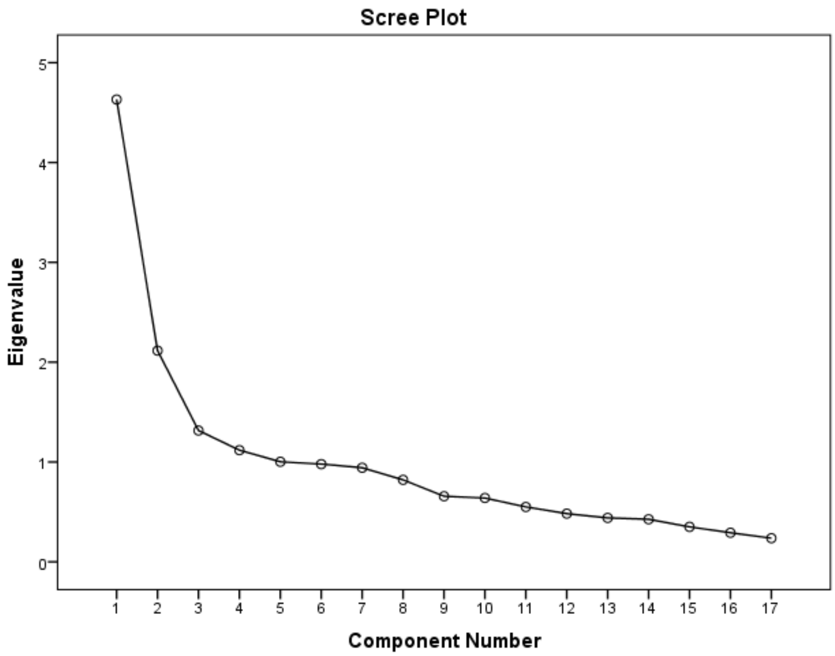


Table 4.1. Communalities for Two- and Three-Component Models

Variable	Two-Component Model	Three-Component Model
PRIORI	.759	.734
PRESSU	.719	.729
ALLKNO	.690	.659
ENCOUR	.628	.615
CNTNLR	.610	.469
LESPLN	.594	.451
DISCHD	.578	.485
CURRDV	.541	.359
INDCHD	.538	.264
SCHSPR	.463	.477
ACCPTD	.383	.394
MISSIO	.348	.350
SCHPLC	.339	.248
CNTRLC	.338	.094
STNDLO (reverse coded)	.229	.234
NOTCAP (reverse coded)	.127	.082
COMMTE	.034	.032

Although seven variables had communalities less than .4, which suggests that these variables would struggle to load on any of the factors extracted, the pattern matrix demonstrated that only three variables—CNTRLC, NOTCAP, and COMMTE—failed to load on any of the factors in the two-factor model or three-factor model (Table 4.2). Based on the scree plot and the limited additional variance explained by the third factor, a two-factor model was selected.[1] As a result, PCA was conducted again without the variables listed above (Table 4.3). Based on the questionnaire items that comprised each factor, these components have been labeled teacher collaboration and school climate.

Table 4.2. Component Loadings for Two- and Three-Component Models with 17 Variables

	Pattern Matrix				
Component	**Two-Component Model**		**Three-Component Model**		
	1	**2**	**1**	**2**	**3**
PRESSU	.806	-.078	.905	-.046	.003
PRIORI	.805	-.066	.914	-.060	.017
ENCOUR	.792	-.066	.805	.055	-.007
ALLKNO	.792	-.058	.874	-.028	.018
SCHSPR	.645	.073	.140	.650	.000
MISSIO	.642	-.010	.355	.393	-.032
SCHPLC	.546	.057	.267	.374	.031
CNTNLR	.530	.201	-.066	.743	.099
STNDLO (reverse coded)	.513	.029	.123	.503	-.027
ACCPTD	.484	.135	-.163	.801	.017

[1] The results of the CFA presented in Appendix B also indicated a high correlation between the second and third factors.

Table 4.2. Component Loadings for Two-Component and Three-Component Models with 17 Variables—Continued

Pattern Matrix					
	Two-Component Model		Three-Component Model		
Variable	**1**	**2**	**1**	**2**	**3**
CNTRLC	.348	-.010	.022	.414	-.063
NOTCAP (reverse coded)	.316	-.066	-.065	.479	-.135
LESPLN	.013	.762	-.015	.015	.766
CURRDV	.009	.710	.018	-.028	.722
COMMTE	.007	.089	.033	-.032	.097
INDCHD	.000	.773	-.009	-.009	.781
DISCHD	-.011	.644	.013	-.046	.657
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					
Rotation converged in 3 iterations.					

Table 4.3. Component Loadings for Two-Component Model with 14 Variables

Pattern Matrix		
	Component	
Variable	**1**	**2**
PRIORI	.819	-.078
PRESSU	.814	-.087
ALLKNO	.807	-.069
ENCOUR	.795	-.072
SCHSPR	.646	.073
MISSIO	.645	-.012
CNTNLR	.542	.197
SCHPLC	.531	.061
STNDLO (reverse coded)	-.507	-.035
ACCPTD	.482	.137

Table 4.3. Component Loadings for Two-Component Model with 14 Variables—Continued

Pattern Matrix		
	Component	
Variable	1	2
LESPLN	.030	.760
CURRDV	.025	.709
INDCHD	.014	.772
DISCHD	.005	.640
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.		
Rotation converged in 3 iterations.		

Hierarchical Cross-Classified Modeling (HCM)

After PCA was used to establish the PLC variables related to teacher collaboration and school climate, HCM was used to answer the research questions by analyzing the relationship between PLCs on students' reading and mathematics performance, and whether those relationships are moderated by student and school characteristics. In this study, students were taught by multiple teachers during their elementary school years, and students' scores on the reading and math direct assessments from kindergarten to fifth grade belong to a combination of students and teachers (Bryk & Raudenbush, 2002). As a result, HCM was used to account for students' mobility across grades and teachers. The sample was restricted to data obtained from students while they remained in their original school.

Data for the HCM analysis came from a number ECLS-K sources: student performance in reading and mathematics from the direct child assessments, student-level data from the parent interview, teacher-level data from the teacher questionnaire, and school-level data from the administrator questionnaire. Three levels of analysis were employed in this study. At level 1, students' reading and mathematics performance was modeled as a function of time between kindergarten and fifth grade. At level 2, performance was modeled as a function of student and teacher characteristics, such as SES and race. Finally, performance was modeled as a function of school type at level 3. Several of the school-level variables were time variant, and as a result, school size, minority enrollment, and FRPL eligibility were modeled at level 2. The ICC for the reading model is .21 at the classroom level and .07 at the school level; 21 percent of the variation in students' reading performance can be attributed to classrooms and 7 percent can be attributed to schools. For the mathematics model, the ICC is .19 at the classroom level and .08 at the school level; 19 percent of the variation in students' mathematics performance can be attributed to classrooms and 8 percent can be attributed to schools. The fact that several time-variant school-level variables (e.g., minority enrollment) were modeled at the classroom level is presumably influencing these results. The fully conditional models are presented below.

Research Question 1

The following model was used to analyze the effects of the PLC and other salient variables on students' reading performance. The same model was used to analyze the effects of the PLC variables on students' mathematics performance with the mathematics IRT scale score as the outcome variable. Data were weighted and continuous variables were centered on the grand mean. Cumulative effects models were used to account for the carryover of treatment effects across years.

$$
\begin{aligned}
RSCORE_{ijkl} = {} & \delta_{000} + \delta_{001}\text{*SCTYP\_PR}_{kl} + \delta_{010}\text{*GENDER\_M}_{jl} + \delta_{020}\text{*AVESES}_{jl} + \\
& \delta_{030}\text{*ATRISK\_R}_{jl} + \delta_{040}\text{*RACE\_BHO}_{jl} + \delta_{050}\text{*PLC\_TC}_{jl} + \delta_{060}\text{*PLC\_SC}_{jl} + \\
& \delta_{070}\text{*AVESAT}_{jl} + \delta_{080}\text{*HGHSTD\_A}_{jl} + \delta_{090}\text{*ENRLS\_S}_{jl} + \delta_{0100}\text{*ENRLS\_L}_{jl} + \\
& \delta_{0110}\text{*MINOR3\_L}_{jl} + \delta_{0120}\text{*MINOR3\_H}_{jl} + \delta_{0130}\text{*FRPL\_M\_S}_{jl} + \delta_{100}*TIME\_R_{ijkl} + \\
& \delta_{101}*TIME\_R_{ijkl}\text{*SCTYP\_PR}_{kl} + \delta_{110}*TIME\_R_{ijkl}\text{*GENDER\_M}_{jl} + \\
& \delta_{120}*TIME\_R_{ijkl}\text{*AVESES}_{jl} + \delta_{130}*TIME\_R_{ijkl}\text{*ATRISK\_R}_{jl} + \\
& \delta_{140}*TIME\_R_{ijkl}\text{*RACE\_BHO}_{jl} + \delta_{150}*TIME\_R_{ijkl}\text{*PLC\_TC}_{jl} + \\
& \delta_{160}*TIME\_R_{ijkl}\text{*PLC\_SC}_{jl} + \delta_{170}*TIME\_R_{ijkl}\text{*AVESAT}_{jl} + \\
& \delta_{180}*TIME\_R_{ijkl}\text{*HGHSTD\_A}_{jl} + \delta_{190}*TIME\_R_{ijkl}\text{*ENRLS\_S}_{jl} + \\
& \delta_{1100}*TIME\_R_{ijkl}\text{*ENRLS\_L}_{jl} + \delta_{1110}*TIME\_R_{ijkl}\text{*MINOR3\_L}_{jl} + \\
& \delta_{1120}*TIME\_R_{ijkl}\text{*MINOR3\_H}_{jl} + \delta_{1130}*TIME\_R_{ijkl}\text{*FRPL\_M\_S}_{jl} + \\
& b_{10jl}*TIME\_R_{ijkl} + c_{10kl}*TIME\_R_{ijkl} + d_{10l}*TIME\_R_{ijkl} + e_{ijkl}
\end{aligned}
$$

The results of this model are presented in table 4.4. The average initial reading IRT scale score for individuals with all reference variable characteristics (e.g., female, white or Asian, not academically at risk…) was 36.08 at the .001 level, significantly greater than 0. With respect to student characteristics, being male had a significant negative effect on initial reading scores (-1.08, $p < .001$) and growth in reading scores (-.43, $p < .01$). Similarly, being academically at-risk also had a significant negative effect on initial reading scores (-7.43, $p < .001$) and growth (-7.34, $p < .001$). Conversely, students' SES had a significant positive effect on initial reading scores (2.94, $p < .001$) and growth in reading scores (.94, $p < .001$).

With respect to school characteristics, being a student in a small school with fewer than 300 students was associated with significantly higher initial reading scores (.91, $p < .05$) but significantly slower growth in reading scores (-1.83, $p < .001$) when compared to students in mid-sized schools (i.e., schools with 300–749 students). Being enrolled in a large school with 750 or more students was not significantly associated with initial reading scores, but it was associated with significant growth in reading scores (.77, $p = .01$). The percentage of FRPL-eligible students at a student's school was associated with significantly lower initial reading scores (-0.03, $p < .001$). Neither school type nor minority enrollment demonstrated significant effects on initial student reading scores or growth in reading scores.

Finally, based on prior research, the hypothesis is that PLCs will have a small, but significantly positive effect on elementary school student reading performance. The hypothesis was supported for school climate on initial reading scores (.99, $p < 0.01$) and teacher collaboration on the growth of reading scores (1.08, $p < 0.001$). The hypothesis was not supported for school climate on the growth of reading scores (-.61, $p < 0.05$) or teacher collaboration on the initial reading scores (-.67, $p < 0.01$).

Table 4.4. Effects of PLCs on Student Reading Performance

Fixed effects	Coefficient	SE	*t*-ratio	df
Intercept	36.081141***	1.518128	23.767	12384
Gender – Male	-1.082617***	0.264698	-4.090	12384
Race – Black, Hispanic, Other	-0.637202	0.412367	-1.545	12384
SES	2.935535***	0.262239	11.194	12384
At-Risk Status	-7.425196***	0.293960	-25.259	12384
Teacher Advanced Degree	-0.394228	0.331819	-1.188	12384
Teacher Job Satisfaction	0.044209	0.282879	0.156	12384
Teacher Collaboration	-0.673747**	0.255264	-2.639	12384
School Climate	0.992835**	0.376203	2.639	12384
School Enrollment - Small	0.909130*	0.406898	2.234	12384
School Enrollment - Large	-0.196210	0.470820	-0.417	12384
Minority Enrollment - Low	-0.734629	0.457863	-1.604	12384
Minority Enrollment - High	-0.604853	0.548006	-1.104	12384
School FRPL	-0.030080***	0.008372	-3.593	12384
School Type Private	0.716782	0.560878	1.278	29013
Time (Slope)	31.359766***	0.984257	31.861	872
Gender - Male	-0.430320**	0.157510	-2.732	12384
Race – Black, Hispanic, Other	-0.385558	0.232122	-1.661	12384
SES	0.940394***	0.142569	6.596	12384

Table 4.4. Effects of PLCs on Student Reading Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
At-Risk Status	-7.341053***	0.226693	-32.383	12384
Teacher Advanced Degree	-0.653280**	0.229842	-2.842	12384
Teacher Job Satisfaction	-1.248240***	0.181259	-6.886	12384
Teacher Collaboration	1.077950***	0.186628	5.776	12384
School Climate	-0.613549*	0.306114	-2.004	12384
School Enrollment - Small	-1.828179***	0.417210	-4.382	12384
School Enrollment - Large	0.774681**	0.301630	2.568	12384
School Minority Enrollment – Low	-0.422985	0.351766	-1.202	12384
School Minority Enrollment - High	-0.002352	0.415895	-0.006	12384
School FRPL	-0.011174	0.006807	-1.642	12384
School Type - Private	-0.587119	0.488754	-1.201	872

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

The following hierarchical cross-classified model was used to analyze the effects of the PLC and other salient variables on students' mathematics performance. The results of this model are presented in table 4.5.

$$
\begin{aligned}
&\mathit{MSCORE}_{ijkl} = \delta_{000} + \delta_{001}\text{*SCTYP\_PR}_{kl} + \delta_{010}\text{*GENDER\_M}_{jl} + \delta_{020}\text{*AVESES}_{jl} + \\
&\delta_{030}\text{*ATRISK\_R}_{jl} + \delta_{040}\text{*RACE\_BHO}_{jl} + \delta_{050}\text{*PLC\_TC}_{jl} + \delta_{060}\text{*PLC\_SC}_{jl} + \\
&\delta_{070}\text{*AVESAT}_{jl} + \delta_{080}\text{*HGHSTD\_A}_{jl} + \delta_{090}\text{*ENRLS\_S}_{jl} + \delta_{0100}\text{*ENRLS\_L}_{jl} + \\
&\delta_{0110}\text{*MINOR3\_L}_{jl} + \delta_{0120}\text{*MINOR3\_H}_{jl} + \delta_{0130}\text{*FRPL\_M\_S}_{jl} + \delta_{100}\text{*}\mathit{TIME\_R}_{ijkl} + \\
&\delta_{101}\text{*}\mathit{TIME\_R}_{ijkl}\text{*SCTYP\_PR}_{kl} + \delta_{110}\text{*}\mathit{TIME\_R}_{ijkl}\text{*GENDER\_M}_{jl} + \\
&\delta_{120}\text{*}\mathit{TIME\_R}_{ijkl}\text{*AVESES}_{jl} + \delta_{130}\text{*}\mathit{TIME\_R}_{ijkl}\text{*ATRISK\_R}_{jl} + \\
&\delta_{140}\text{*}\mathit{TIME\_R}_{ijkl}\text{*RACE\_BHO}_{jl} + \delta_{150}\text{*}\mathit{TIME\_R}_{ijkl}\text{*PLC\_TC}_{jl} + \\
&\delta_{160}\text{*}\mathit{TIME\_R}_{ijkl}\text{*PLC\_SC}_{jl} + \delta_{170}\text{*}\mathit{TIME\_R}_{ijkl}\text{*AVESAT}_{jl} + \\
&\delta_{180}\text{*}\mathit{TIME\_R}_{ijkl}\text{*HGHSTD\_A}_{jl} + \delta_{190}\text{*}\mathit{TIME\_R}_{ijkl}\text{*ENRLS\_S}_{jl} + \\
&\delta_{1100}\text{*}\mathit{TIME\_R}_{ijkl}\text{*ENRLS\_L}_{jl} + \delta_{1110}\text{*}\mathit{TIME\_R}_{ijkl}\text{*MINOR3\_L}_{jl} + \\
&\delta_{1120}\text{*}\mathit{TIME\_R}_{ijkl}\text{*MINOR3\_H}_{jl} + \delta_{1130}\text{*}\mathit{TIME\_R}_{ijkl}\text{*FRPL\_M\_S}_{jl} + \\
&b_{10jl}\text{*}\mathit{TIME\_R}_{ijkl} + c_{10kl}\text{*}\mathit{TIME\_R}_{ijkl} + d_{10l}\text{*}\mathit{TIME\_R}_{ijkl} + e_{ijkl}
\end{aligned}
$$

The average initial mathematics IRT scale score for individuals with all the reference variable characteristics (e.g., female, white or Asian, not academically at risk…) was 26.24 at the .001 level, significantly greater than 0. With respect to student characteristics, being a minority other than Asian had a significant negative effect on students' initial mathematics scores (-1.36, $p < .001$). Being academically at risk also had a significant negative effect on initial mathematics scores (-7.43, $p < .001$) and growth in mathematics scores (-7.18, $p < .001$). While being male was not significantly associated with initial mathematics scores, it did demonstrate a significant positive effect on growth in mathematics scores (1.17, $p < .001$). Students' SES also had a significant positive effect on initial mathematics scores (2.92, p < .001) and growth in mathematics scores (.57, p < .001).

With respect to school characteristics, being a student in a private school was associated with significantly higher initial mathematics scores (1.26, p < .01) but significantly slower growth (-.78, p < .05) when compared to students in public schools. Similarly, being a student in a small school was associated with significantly higher initial mathematics scores (.85, p < .01) but significantly slower growth (-1.82, p < .001) when compared to students in mid-sized schools. Being a student in a low-minority enrollment school (i.e., with fewer than 25 percent minority enrollment) was also associated with significantly higher initial mathematics scores (.74, p < .05). Conversely, the percentage of FRPL-eligible students at a student's school was associated with significantly lower initial mathematics scores (-0.02, p = .001).

Similar to the results from the analysis of reading scores, teacher collaboration had a significant negative effect on initial mathematics scores (-1.36, p < .001), but a significant positive effect on growth in mathematic scores (.78, p < .001). Conversely, school climate had a positive significant effect on initial mathematics scores (.63, p < .05) but a negative although nonsignificant effect on growth in mathematics scores (-.43, p < .07).

Table 4.5. Effects of PLCs on Student Mathematics Performance

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.238957***	1.159556	22.628	11995
Gender – Male	-0.019138	0.205093	-0.093	11995
Race – Black, Hispanic, Other	-1.358275***	0.297436	-4.567	11995
SES	2.919758***	0.200872	14.535	11995

Table 4.5. Effects of PLCs on Student Mathematics Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
At-Risk Status	-7.434708***	0.209993	-35.405	11995
Teacher Advanced Degree	-0.129481	0.241284	-0.537	11995
Teacher Job Satisfaction	0.184437	0.219961	0.839	11995
Teacher Collaboration	-1.358275***	0.297436	-4.567	11995
School Climate	0.628427*	0.312872	2.009	11995
School Enrollment - Small	0.848693**	0.321379	2.641	11995
School Enrollment - Large	0.284665	0.357228	0.797	11995
Minority Enrollment - Low	0.741701*	0.368129	2.015	11995
Minority Enrollment - High	-0.442449	0.372161	-1.189	11995
School FRPL	-0.020895***	0.006256	-3.340	11995
School Type Private	1.263110**#	0.461685	2.736	28711
Time (Slope)	24.833362***	0.764779	32.471	872
Gender - Male	1.170750***	0.123538	9.477	11995
SES	0.565930***	0.115369	4.905	11995
Race – Black, Hispanic, Other	-0.291322	0.189393	-1.538	11995
At-Risk Status	-7.184456***	0.169588	-42.364	11995
Teacher Advanced Degree	-0.509603**	0.167198	-3.048	11995
Teacher Job Satisfaction	-0.987579***	0.140623	-7.023	11995

Table 4.5. Effects of PLCs on Student Mathematics Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Teacher Collaboration	0.779027***	0.141073	5.522	11995
School Climate	-0.432386	0.237155	-1.823	11995
School Enrollment - Small	-1.819595***	0.303274	-6.000	11995
School Enrollment - Large	0.634632**	0.241933	2.623	11995
School Minority Enrollment - Low	-0.474151	0.277075	-1.711	11995
School Minority Enrollment - High	-0.305565	0.318659	-0.959	11995
School FRPL	0.000800	0.005490	0.146	11995
School Type - Private	-0.780931*	0.379982	-2.055	872

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Research Question 2

The second and third research questions were analyzed by running separate HCM models with interaction terms. Interactions between student-level characteristics (race, SES, at-risk status) and the two PLC variables (teacher collaboration and school climate) were modeled to answer the second research question. The hypothesis that PLCs would have differential effects on students with the greatest effects observed for white students, higher-SES students, and students who are not considered academically at risk is not supported for reading. None of the interactions between student-level characteristics and the PLC variables is significant: the effects of the PLC variables did not vary significantly by students' race, SES, or at-risk status (tables 4.6, 4.8, and 4.10). With respect to mathematics, the hypothesis that PLCs would have greater effects for students who were not academically at risk is supported for the measures of teacher collaboration and school climate (table 4.11). Being academically at risk significantly lowered the effect of teacher collaboration (-.70, p < .01) and a positive school climate (-.99, p < .01) on mathematics scores.

Table 4.6. Interaction of Race and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept	36.158660***	1.543375	36.099131***	1.520520
PLC	-0.714953**	0.282401	0.871628*	0.413035
Race – Black, Hispanic, Other	-0.948271	0.826891	-0.674700	0.415020
Time (Slope)	31.372068***	0.983609	31.349090***	0.985439
PLC	1.075448***	0.186704	-0.626254*	0.308464
Race – Black, Hispanic, Other	-0.396560	0.234158	-0.375869	0.232838
Race - Black, Hispanic, Other * PLC	0.151566	0.347617	0.403035	0.564147

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.7. Interaction of Race and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept	26.323087***	1.189186	26.220671***	1.160514
PLC	-0.598417**	0.235619	0.752915*	0.351046
Race – Black, Hispanic, Other	-1.669310**	0.609672	-1.322562***	0.297090
Time (Slope)	24.843758***	0.763271	24.843431***	0.766200
PLC	0.777734***	0.141037	-0.424254	0.237305
Race – Black, Hispanic, Other	-0.302583	0.191477	-0.301680	0.189428
Race – Black, Hispanic, Other * PLC	0.151528	0.269141	-0.374330	0.391429

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.8. Interaction of SES and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept	36.376030***	1.301281	36.403687***	1.515342
PLC	-0.671660**	0.229320	0.989127**	0.384952
SES	3.265659***	0.452114	2.938950***	0.261464
Time (Slope)	31.285562***	0.878835	31.266827***	0.984489
PLC	1.073440***	0.154744	-0.613741*	0.306295
SES	0.952868***	0.138231	0.939533***	0.141023
SES * PLC	-0.161724	0.196912	-0.029800	0.378164

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.9. Interaction of SES and PLC Variables - Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept	26.435929***	1.153816	26.415615***	1.159113
PLC	-0.552085**	0.206658	0.663631*	0.320214
SES	2.612436***	0.440773	2.893137	0.197702
Time (Slope)	24.766151***	0.764953	24.780547***	0.765218
PLC	0.781240***	0.141001	-0.434118***	0.237170
SES	0.553676***	0.116557	0.573768***	0.115121
SES * PLC	0.150613	0.205567	0.235850	0.282812

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.10. Interaction of At-Risk Status and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**
Intercept	35.958700***	1.522651	36.076955***	1.517969
PLC	-0.597929*	0.272773	1.127965**	0.418118
At Risk	-6.441143***	0.744425	-7.405340***	0.293065
Time (Slope)	31.323174***	0.986322	31.363749***	0.984633
PLC	1.084302***	0.186868	-0.607632*	0.306960
At Risk	-7.308703***	0.226123	-7.359811***	0.226779
At Risk * PLC	-0.482417	0.324547	-0.698937	0.504642

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.11. Interaction of At-Risk Status and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	26.050024***	1.171716	26.254359***	1.160527
PLC	-0.428941*	0.223179	0.841685**	0.342986
At Risk	-6.003549***	0.498301	-7.399965***	0.209021
Time (Slope)	24.792903***	0.765635	24.836771***	0.765334
PLC	0.782251***	0.141163	-0.429547	0.237604
At Risk	-7.138293***	0.169502	-7.210230***	0.170102
At Risk * PLC	-0.704950**	0.226668	-0.992935**	0.350469

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Research Question 3

Interactions between several school-level characteristics (school size, school minority enrollment, FRPL eligibility, and school type) and the two PLC variables were modeled to answer the third research question. The first three school-level characteristics were modeled at the teacher level because of their variability across data collection periods. The hypothesis that larger schools, schools with higher minority enrollment, lower SES schools, and public schools would reduce the influence of PLCs on student performance is not supported by the data for reading or mathematics. The effects of the PLC variables did not vary significantly by a school's minority enrollment, percentage of FRPL-eligible students, or school type (tables 4.14–4.19). Only one of the school-level interactions was significant: being in a small school reduced the effect of teacher collaboration on mathematics performance (-1.19, $p < .01$) (table 4-13).

Table 4.12. Interaction of School Enrollment and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	35.598578***	1.555859	36.086582***	1.518622
PLC	-0.450906	0.307624	1.063642*	0.487220
Enrollment - Small	2.492043**	0.960553	1.001506	2.203240
Enrollment - Large	-0.197778	1.364633	0.606888	1.932435
Time (Slope)	31.413783***	0.986897	31.356831***	0.984234
PLC	1.050869***	0.188325	-0.611590*	0.309065
Enrollment - Small	-1.741655***	0.424617	-1.830394***	0.416163
Enrollment - Large	0.782734**	0.301977	0.764674**	0.302068
Enrollment Small * PLC	-0.837768	0.460655	-0.033083	0.818251
Enrollment Large * PLC	-0.001741	0.580383	-0.304732	0.741646

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.13. Interaction of School Enrollment and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	25.381930***	1.153900	26.245941***	1.160482
PLC	-0.146345	0.230473	0.730055*	0.368796
Enrollment - Small	3.133474***	0.764258	0.289375	1.544937
Enrollment - Large	1.620907	0.951284	2.297519	1.663140
Time (Slope)	24.872191***	0.763434	24.827855***	0.765380
PLC	0.752933***	0.141493	-0.414933	0.237472
Enrollment - Small	-1.698518***	0.307188	-1.818265***	0.304133
Enrollment - Large	0.660890**	0.241663	0.615224**	0.244037

Table 4.13. Interaction of School Enrollment and PLC Variables – Mathematics—Continued

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Enrollment Small * PLC	-1.194998**	0.368428	0.214418	0.583380
Enrollment Large * PLC	-0.632306	0.399036	-0.770962	0.621061

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.14. Interaction of School Minority Enrollment and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	35.982765***	1.754476	36.240749***	0.825533
PLC	-0.629308	0.485407	1.288407	0.716084
Minority Enrollment - Low	-0.531311	1.140281	0.062920	2.136166
Minority Enrollment - High	-0.998441	1.454593	1.257098	2.514855
Time (Slope)	31.376017***	0.985612	25.956629***	0.626406
PLC	1.071475***	0.188396	-0.605751**	0.309018
Minority Enrollment - Low	-0.413671	0.354407	-0.430013	0.351744
Minority Enrollment - High	-0.012651	0.414842	-0.027103	0.418312
Minority Enrollment - Low * PLC	-0.100779	0.497214	-0.297456	0.791328
Minority Enrollment - High * PLC	0.206627	0.662464	-0.708018	0.919020

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.15. Interaction of School Minority Enrollment and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 3: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	25.954420***	1.262327	27.020421***	0.609688
PLC	-0.421669	0.353663	0.788212	0.530272
Minority Enrollment - Low	1.165318	0.797890	1.380243	1.558976
Minority Enrollment - High	-0.445749	0.895973	-0.144691	1.663993
Time (Slope)	24.8407428**	0.764391	20.553151***	0.493863
PLC	0.774786***	0.141536	-0.437306	0.237031
Minority Enrollment - Low	-0.455226	0.279785	-0.481198	0.277567
Minority Enrollment - High	-0.303288	0.319390	-0.310126	0.317666
Minority Enrollment - Low * PLC	-0.207917	0.367604	-0.236155	0.584022
Minority Enrollment – High * PLC	0.011130	0.430849	-0.108451	0.631990

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.16. Interaction of School FRPL and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	37.185044***	1.839148	36.085462***	1.518355
PLC	-0.909913**	0.346984	0.961014	0.549049
FRPL	-0.046931**	0.016544	-0.032564	0.028292
Time (Slope)	31.428759**	0.987393	31.357918***	0.984705
PLC	1.064622***	0.187356	-0.615325*	0.308035
FRPL	-0.011529	0.006821	-0.011135	0.006833
FRPL * PLC	0.007941	0.006906	0.000930	0.010125

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.17. Interaction of School FRPL and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	26.457414***	1.471798	26.216379***	1.159400
PLC	-0.601404*	0.299933	0.848136	0.456476
FRPL	-0.024143*	0.012564	-0.004751	0.020697
Time (Slope)	24.846412***	0.763474	24.843839***	0.765416
PLC	0.777002***	0.140748	-0.424618	0.237349
FRPL	0.000727	0.005505	0.000578	0.005496
FRPL * PLC	0.001537	0.005300	-0.006075	0.007538

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.18. Interaction of School Type and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	35.981595***	1.535951	36.079695***	1.518194
PLC	-0.630780*	0.269471	0.962417*	0.396136
School Type - Private	1.107674	1.116792	0.681437	0.580691
Time (Slope)	31.370429	0.984509	31.359020***	0.984197
PLC	1.073399***	0.186868	-0.611233*	0.306138
School Type - Private	-0.569423	0.493882	-0.578688	0.488285
School Type – Private * PLC	-0.213956	0.551688	0.188008	0.930032

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table 4.19. Interaction of School Type and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: School Climate	
	Coefficient	SE	Coefficient	SE
Intercept	25.945965***	1.134065	26.236078***	1.159399
PLC	-0.430766*	0.195070	0.569066	0.307927
School Type - Private	2.415945**	0.974736	1.189805**	0.480697
Time (Slope)	24.869310***	0.760573	24.832430***	0.764842
PLC	0.765838***	0.139464	-0.428699	0.236415
School Type - Private	-0.729844	0.386716	-0.763238*	0.381387
School Type – Private * PLC	-0.632809	0.531493	0.387512	0.828855

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Discussion

This chapter summarizes the analysis examining the effect of PLCs on students' performance in reading and mathematics. Additionally, this study explored whether the relationship between PLCs and student performance is moderated by student and school characteristics. Using PCA, I developed two PLC variables from the teacher questionnaire data: teacher collaboration and school climate. The hypothesis that PLCs would have a significantly positive effect on elementary school students' reading and mathematics performance was partially supported. Teacher collaboration had a significantly positive effect on the growth of students' reading and mathematics performance from kindergarten to fifth grade. However, teacher collaboration had a significantly negative association with students' initial reading and mathematics performance. This could be a result of teachers collaborating more frequently when teaching lower-performing students. A positive school climate, on the other hand, was associated with higher initial reading and mathematics performance in kindergarten, but slower growth, significantly so for reading. It could be that the positive association with initial performance left little room for improvement with respect to growth. Nevertheless, these two PLC variables—teacher collaboration and school climate—are not negatively correlated, and their relationship and opposite effects on students' initial performance and growth is worthy of further exploration.

Regarding the interaction models, the analysis did not support most of the hypotheses regarding student- and school-level effects as moderators of the relationship between PLCs and student performance. Only two of the interactions between the PLC variables and the student- and school-level variables had significant effects. With respect to the student-level characteristics, none of the student-level characteristics moderated the effect of PLCs on reading performance. For mathematics, only being academically at-risk significantly moderated the effect of the PLC variables, lowering the effect of teacher collaboration and a positive school climate on student performance in mathematics as hypothesized. Academically at-risk students are routinely performing in the bottom quartile across data collection periods. They can reasonably be expected to require a significant investment of time and resources to show even small academic gains, which could explain why being at-risk reduces the influence of PLCs.

With respect to the school-level characteristics, minority enrollment, percentage of FRPL-eligible students, and school type did not moderate the relationship between PLCs and student performance in either reading or mathematics. However, being in a small school significantly lowered the effect of teacher collaboration in mathematics, contrary to the hypothesis. On average, students in small schools performed significantly better in mathematics than students in medium-sized schools. Therefore, it may be that the performance of students in small schools is less sensitive to the influence of PLCs because they are already performing at a higher level.

PLCs may work relatively equitably across different student groups and schools to improve student instruction. Alternatively, the results may reflect one or more of the study limitations, and each of the limitations provides an important consideration for future research. First, it may be the case that the PLC variables are not sufficiently robust to show moderating effects. As noted previously, the ECLS-K was not specifically designed to research the effects of PLCs, although some PLC-related items were included in the teacher questionnaires. Additionally, the PLC variables reflect teachers' perceptions of PLC dimensions at their school, and no attempt was made to validate those perceptions (e.g., comparing responses by teachers at the same school). Student attrition is also a serious concern in longitudinal studies like this one, and at least with respect to students' performance in reading, the analytic sample does differ significantly from the full sample, potentially leading to biased results.

Finally, the lack of significant interaction effects may be due to a lack of statistical power. Statistical power is the ability to detect an effect if an effect exists (Park, 2004). Ideally, a sample will be large enough to detect an effect, but not so large as to detect small but statistically significant differences that have no practical importance. Power analysis is more complicated when using multilevel models, in part because each level of a model has its own sample size (e.g., the number of students, teachers, and schools) (Grace-Martin, n.d.). A further complicating factor is that the current study examines cross-level interactions (e.g., between teacher collaboration and student characteristics). Although the current study examines data from thousands of students in hundreds of schools, conducting a power analysis would be an important next step to confirm sufficient sample sizes to detect effects.

CHAPTER 5

CONCLUSION

"It is virtually impossible to create and sustain over time conditions for productive learning for students when they do not exist for teachers." (Sarason, 1996)

Introduction

This study examines the effect of professional learning communities on elementary school students' performance in reading and mathematics using data from the ECLS-K. This study also investigates whether professional learning communities have differential effects on student performance based on student and school characteristics. Specifically, this study answers the following research questions:

1) What is the effect of PLCs on elementary students' performance in reading and mathematics?
2) Do PLCs have differential effects on students' reading and mathematics performance based on the following student characteristics: socioeconomic background, race, and at-risk status?
3) Do PLCs have differential effects on students' reading and mathematics performance based on the following school characteristics: school type, school size, minority enrollment, and percentage of students eligible for free and reduced price lunch?

The theory is that PLCs affect student achievement indirectly by strengthening teachers' professional network with their colleagues, thereby reducing the stress and burnout caused by teachers' physical and social isolation, increasing social support for teacher learning, increasing teacher commitment and effort, and improving instruction. PCA was used to examine individual items from the teacher questionnaires and identify correlations among the variables reflecting dimensions of PLCs. HCM was then used to analyze whether the PLC constructs, controlling for other student-, teacher-, and school-level variables, had an impact on students' IRT scale scores in reading and mathematics.

Summary of Findings

Using PCA, two PLC variables were identified. The teacher collaboration variable measures an essential element of PLCs: how frequently teachers meet with one another to discuss and work together on instructional issues. The school climate variable reflects a wider array of PLC elements including trust, respect, openness to learning, shared values, and a focus on student learning, as well as the extent to which teachers agreed that their principal created a supportive working environment. After controlling for student- and school-level variables, HCM analysis indicated that teacher collaboration had a significantly positive effect on the growth of students' reading and mathematics performance from kindergarten to fifth grade. A positive school climate was associated with significantly higher initial reading performance in kindergarten. These findings support the hypothesis that PLCs can have a significantly positive effect on student performance.

However, the two PLC variables also demonstrated negative effects on student achievement. Specifically, teacher collaboration was associated with significantly lower initial reading and mathematics performance, whereas school climate was associated with slower growth, significantly so for reading. It is reasonable to theorize that teacher collaboration was higher in classrooms with lower-performing students who needed greater assistance; teachers of these students may have sought out more advice and support from their colleagues than teachers of higher-performing students. With respect to school climate, teachers of higher-performing students more strongly agreed that they were in a supportive school environment than teachers of lower-performing students, at least initially. It is possible that the negative association between school climate and growth in students' reading and mathematics performance was a result of having little room to improve. An open question, and an interesting one to explore, is why did two variables that are intended to measure different but complementary elements of PLCs demonstrate opposite effects from one another on student performance?

With respect to whether the effect of PLCs varies by student population (e.g., low-SES students versus high-SES students), this was rarely the case. Of the student-level characteristics, only being academically at risk significantly moderated the effect of the PLC constructs on mathematics performance, lowering the effect of teacher collaboration and a positive school climate on student performance in mathematics as hypothesized. Of the school-level characteristics, only being in a small school significantly lowered the effect of teacher collaboration in mathematics, contrary to the relationship that was hypothesized. This could be because PLCs may have similar benefits for students regardless of the student- and school-level characteristics tested in this study. Alternatively, limitations of the current study may have prevented finding differential effects—for example, a lack of statistical power or bias in the analytic sample. While the study appears to be biased in reading, with significantly higher performers in the analytic sample than the full sample, the results are similar across reading and mathematics.

Conclusions

Barriers to teacher learning are barriers to student learning. One longstanding barrier is the physical and social isolation of teachers from their colleagues. Rosenholtz called teachers' professional isolation "probably the greatest impediment to learning to teach" (1989, p. 878). As a result, researchers have advocated for measures of teacher professionalization, such as creating PLCs, as effective ways to shape teacher practice and move the needle on student achievement. In this view, collegial relationships are seen as an important avenue of communication, influence, and reform (Bidwell & Yasumoto, 1997; Kruse, Louis, & Bryk, 1995). The advantages of PLCs, in this regard include teachers' increased responsibility for performance, increased personal commitment to work, and values that promote self-regulation (Kruse et al., 1996).

Several key organizations in the education field have emphasized the importance of collaborative working environments for teachers and their benefits to students, including the U.S. Department of Education, the National Board for Professional Teaching Standards, and Learning Forward. There appears to be agreement coalescing around a need to better support teachers and schools in their efforts to improve student learning. On the other hand, not everyone believes that PLCs are a promising reform effort. For example, in his book *So Much Reform, So Little Change: The Persistence of Failure in Urban Schools*, Payne argues that collegial interactions are not enough to solve the problems our schools face (2008). Others argue that the research often paints too rosy a picture of PLCs and glosses over the challenges with respect to establishing and sustaining them, as well as the specific character of each community, all criticisms that have implications for school reform (Achinstein, 2002; Westheimer, 1999). In addition, the current study focuses on elementary schools, and it is a common belief that schoolwide PLCs are easier to implement at the elementary level than the secondary level (Lee & Smith, 1996; Visscher & Witziers, 2004). Some of the literature on secondary schools suggests that the departmental nature of secondary schools undermines attempts to promote schoolwide PLCs (Lee & Smith, 1996; Visscher & Witziers, 2004).

The literature indicates that implementing PLCs is complex. PLCs push teachers to think about their practice in new ways (Vescio et al., 2008). The methodological and practical challenges of defining, measuring, and fostering professional learning communities cannot be understated. However, PLCs are not meant to be a stand-alone reform; rather they serve as one way to restructure teachers' work to promote teacher—and therefore student—learning. Regardless of whether they are called learning communities, professional learning communities, communities of practice, or something else, this research and other studies on PLCs provide evidence that a fundamental restructuring of teachers work toward a more collaborative, supportive professional environment appears promising.

Significance and Limitations of the Study

The ECLS-K is a rich source of data on a cohort of students and the multitude of factors that affect students' academic, social, emotional, and physical health-related outcomes (Tourangeau, Nord, Le, Sorongon, & Najarian, 2009). The sample comprises students from public and private schools and diverse socioeconomic, racial, and ethnic backgrounds. The study design allows researchers to follow a cohort of students over the course of a decade and link student-level data to data on families, teachers, and schools on a vast array of topics.

The findings from this study contribute to the field in several ways. First, the study addresses the need for more empirical evidence on the impact of PLCs on student performance using a large, national dataset. Research on the effects of PLCs has primarily been descriptive and has provided the education community with a great deal of knowledge about how to implement and facilitate PLCs. However, few studies have examined the impact of PLCs on instructional practices or student achievement (Lomos et al., 2011; Stoll, 2006; Vescio et al., 2008). Studies that have examined the impact on student achievement are often restricted to a single school or school district and do not link student data to teacher data, thereby limiting generalizability. Ultimately, in order to make a strong case that PLCs are worth the investment, researchers must provide evidence that PLCs improve student performance, which this study does.

Second, this study adds to the literature on organizational characteristics that may mediate the effect of PLCs. Previous research has demonstrated the powerful effect of student characteristics, particularly family income, on school achievement (Coleman, 1966; Reardon, 2011). While research has been conducted on how some organizational characteristics facilitate or impede PLCs, there is no clear consensus in terms of characteristics such as school size and type, and limited research on minority enrollment and school-level SES. The findings from this study suggest that PLCs can act equitably across different types of student populations and schools to improve student performance; however, more research in this area is needed.

Finally, there is a great deal of discussion on reforming teacher professional development to emphasize sustained, job-embedded, reflective dialogue and collaboration focused on student learning. Organizations such the National Board for Professional Teaching Standards (NBPTS) and Learning Forward (formerly known as the National Staff Development Council) include participation in learning communities in their key standards for teacher practice. Moreover, in the most recent reauthorization of the ESEA, the U.S. Department of Education specified that teacher professional development should be “intensive, collaborative, job-embedded, data-driven, and classroom-focused," essential features of PLCs (S. 1177, Section 8002, page 295, paragraph 42). Although there appears to be agreement coalescing around a need to better support teachers and schools in their efforts to improve student learning, more research on effective ways to provide that support is still needed. This study provides evidence that PLCs are a promising way to provide teachers with the support they need to better serve their students.

Several limitations of this study are worth noting. First, attrition is a common concern with longitudinal studies like the ECLS-K. The ECLS-K began with 21,387 students in the fall of kindergarten and had 16,143 students participating in the study by the fifth-grade data collection. In addition, the analytic samples in the current study are restricted to data from students while they remained in the school where they were initially sampled. For example, if a student changed schools in third grade, data from kindergarten and first grade were used in the analysis. Fifth-grade students who were randomly assigned to have their science teacher as opposed to their mathematics teacher complete a questionnaire were also excluded from the mathematics analysis. T-test comparisons on weighted student data suggest no significant differences between students in the analytic sample and the full sample on several student characteristics; however, there was a significant difference between the samples in students' reading performance with the analytic sample having a significantly higher average IRT scale score than the full sample.

Moreover, although the ECLS-K covered a wide range of topics important to the education community, it could not cover these topics in great depth without increasing costs and risking lower response rates. As a result, the set of questionnaire items included in the study do not fully capture all elements of PLCs. For example, there were three yes/no items in the early rounds of data collection that asked teachers about deprivatized practice such as peer observation, but these items were dropped after the spring first-grade data collection and therefore not included in the current study. In addition, PLC-related items were dropped entirely from the eighth-grade data collection and were not included in the most recent ECLS-K study that began in 2011. Finally, this study relies on teachers' self-reported PLC-related activities, and we do not know the specific nature of these activities. For example, teachers may collaborate frequently to discuss lesson planning or specific children, but we do not know the character or quality of those discussions beyond the overall topic. This reflects Grossman and her colleagues' admonition that a group of teachers in a room together is not necessarily a PLC (2000).

Directions for Future Research

Directions for future research are based on this study's limitations. Over the course of the study, the ECLS-K lost thousands of participating students due to attrition. The current study further excluded students once they changed schools or if they had missing data. Future research on the impact of PLCs on student achievement could use multiple imputation to retain students who have missing data and include school-changers in the analysis to avoid the introduction of selection bias.

This study also used data from the 1998 ECLS-K. As noted, the 2011 ECLS-K, currently in progress, does not include PLC items on the teacher questionnaires. An analysis of more recent data, particularly in light of the continued emphasis on policies that promote more collaborative, job-embedded professional development for teachers, could provide valuable new insights about the extent to which PLCs (or similar reform efforts) are currently implemented and their effects.

Another possible direction for research is to explore the mechanisms of PLCs' effects on student performance. For example, the 1998 ECLS-K teacher questionnaire includes several items related to instruction such as grouping practices, materials and resources used, and specific mathematics activities. The teacher questionnaire also included items like teacher satisfaction, which might be affected by PLCs. Conducting a path analysis would be one method for investigating hypothesized relationships between PLCs, student performance, and the mechanisms by which PLCs affect student performance.

It would also be worth investigating the effects of PLCs using questionnaires specifically designed to measure PLCs. One such instrument is the Professional Learning Communities Survey adapted from the work of Kruse, Louis, and Bryk (1995). The PLC survey assesses the extent to which schools demonstrate the five essential elements of PLCs (i.e., shared values, reflective practice, deprivatized practice, collaboration, and a focus on student learning), as well as the human resources (e.g., trust) and structural conditions (e.g., time to meet) that facilitate PLCs. This survey could be used in conjunction with more specific items on the frequency of teacher collaboration similar to those from the ECLS-K as well as items on the mechanisms of PLCs, such as reduced stress, increased commitment and effort, and improved instructional practices, that have been identified in the existing literature.

In his book, *School Reform from the Inside Out*, Richard Elmore argues that schools cannot simultaneously be the cause and remedy of failure unless there are fundamental changes made to the conditions under which they operate (2004). The implication for those interested in school reform is that reform efforts miss the mark if they simply impose new demands on schools and teachers without also providing the resources needed to build capacity to implement those reforms. This study focuses on one potential mechanism for capacity building—PLCs—and provides evidence for its potential to do what Elmore calls for: fundamentally change the conditions for teaching and learning.

APPENDIX A

DETAILED HCM TABLES

Table A.1. Interaction of Race and Teacher Collaboration - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.158660***	1.543375	23.428	12383
Teacher Collaboration	-0.714953**	0.282401	-2.532	12383
Race – Black, Hispanic, Other	-0.948271	0.826891	-1.147	12383
Time (Slope)	31.372068***	0.983609	31.895	872
Teacher Collaboration	1.075448***	0.186704	5.760	12383
Race – Black, Hispanic, Other	0.151566	0.347617	0.436	12383
Race – Black, Hispanic, Other * Teacher Collaboration	-0.396560	0.234158	-1.694	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.2. Interaction of Race and School Climate - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.099131***	1.520520	23.741	12383
School Climate	0.871628*	0.413035	2.110	12383
Race – Black, Hispanic, Other	-0.674700	0.415020	-1.626	12383
Time (Slope)	31.349090***	0.985439	31.812	872
School Climate	-0.626254**	0.308464	-2.030	12383
Race – Black, Hispanic, Other	-0.375869	0.232838	-1.614	12383

Table A.2. Interaction of Race and School Climate – Reading—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Race – Black, Hispanic, Other * School Climate	0.403035	0.564147	0.714	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.3. Interaction of Race and Teacher Collaboration - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.323087***	1.189186	22.135	11994
Teacher Collaboration	-0.598417**	0.235619	-2.540	11994
Race – Black, Hispanic, Other	-1.669310**	0.609672	-2.738	11994
Time (Slope)	24.843758***	0.763271	32.549	872
Teacher Collaboration	0.777734***	0.141037	5.514	11994
Race – Black, Hispanic, Other	-0.302583	0.191477	-1.580	11994
Race – Black, Hispanic, Other * Teacher Collaboration	0.151528	0.269141	0.563	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.4. Interaction of Race and School Climate - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.220671***	1.160514	22.594	11994
School Climate	0.752915*	0.351046	2.145	11994
Race – Black, Hispanic, Other	-1.322562***	0.297090	-4.452	11994
Time (Slope)	24.843431***	0.766200	32.424	872

Table A.4. Interaction of Race and School Climate – Mathematics—Continued

Fixed effects	Coefficient	SE	t-ratio	df
School Climate	-0.424254	0.237305	-1.788	11994
Race – Black, Hispanic, Other	-0.301680	0.189428	-1.593	11994
Race – Black, Hispanic, Other * School Climate	-0.374330	0.391429	-0.956	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.5. Interaction of SES and Teacher Collaboration - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.376030***	1.509314	24.101	12383
Teacher Collaboration	-0.671660**	0.253922	-2.645	12383
SES	3.265659***	0.576395	5.666	12383
Time (Slope)	31.285562***	0.983643	31.806	872
Teacher Collaboration	1.073440***	0.186724	5.749	12383
SES	0.952868***	0.144134	6.611	12383
SES * Teacher Collaboration	-0.161724	0.245067	-0.660	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.6. Interaction of SES and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.403687***	1.515342	24.023	12383
School Climate	0.989127**	0.384952	2.569	12383
SES	2.938950***	0.261464	11.240	12383
Time (Slope)	31.266827***	0.984489	31.759	872
School Climate	-0.613741*	0.306295	-2.004	12383
SES	0.939533***	0.141023	6.662	12383
SES * School Climate	-0.029800	0.378164	-0.079	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.7. Interaction of SES and Teacher Collaboration - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.435929***	1.153816	22.912	11994
Teacher Collaboration	-0.552085**	0.206658	-2.671	11994
SES	2.612436***	0.440773	5.927	11994
Time (Slope)	24.766151***	0.764953	32.376	872
Teacher Collaboration	0.781240***	0.141001	5.541	11994
SES	0.553676***	0.116557	4.750	11994
SES * Teacher Collaboration	0.150613	0.205567	0.733	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.8. Interaction of SES and School Climate - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.415615***	1.159113	22.790	11994
School Climate	0.663631*	0.320214	2.072	11994
SES	2.893137***	0.197702	14.634	11994
Time (Slope)	24.780547***	0.765218	32.384	872
School Climate	-0.434118	0.237170	-1.830	11994
SES	0.573768***	0.115121	4.984	11994
SES * School Climate	0.235850	0.282812	0.834	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.9. Interaction of At-Risk Status and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	35.958700***	1.522651	23.616	12383
Teacher Collaboration	-0.597929*	0.272773	-2.192	12383
At Risk	-6.441143***	0.744425	-8.653	12383
Time (Slope)	31.323174***	0.986322	31.758	872
Teacher Collaboration	1.084302***	0.186868	5.802	12383
At Risk	-7.308703***	0.226123	-32.322	12383
At Risk * Teacher Collaboration	-0.482417	0.324547	-1.486	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.10. Interaction of At-Risk Status and School Climate - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.076955***	1.517969	23.767	12383
School Climate	1.127965**	0.418118	2.698	12383
At Risk	-7.405340***	0.293065	-25.269	12383
Time (Slope)	31.363749***	0.984633	31.853	872
School Climate	-0.607632*	0.306960	-1.980	12383
At Risk	-7.359811***	0.226779	-32.454	12383
At Risk * School Climate	-0.698937	0.504642	-1.385	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.11. Interaction of At-Risk Status and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.050024***	1.171716	22.232	11994
Teacher Collaboration	-0.428941*	0.223179	-1.922	11994
At Risk	-6.003549***	0.498301	-12.048	11994
Time (Slope)	24.792903***	0.765635	32.382	872
Teacher Collaboration	0.782251***	0.141163	5.541	11994
At Risk	-7.138293***	0.169502	-42.113	11994
At Risk * Teacher Collaboration	-0.704950**	0.226668	-3.110	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.12. Interaction of At-Risk Status and School Climate - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.254359***	1.160527	22.623	11994
School Climate	0.841685**	0.342986	2.454	11994
At Risk	-7.399965***	0.209021	-35.403	11994
Time (Slope)	24.836771***	0.765334	32.452	872
School Climate	-0.429547	0.237604	-1.808	11994
At Risk	-7.210230***	0.170102	-42.388	11994
At Risk * School Climate	-0.992935**	0.350469	-2.833	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.13. Interaction of School Enrollment and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	35.598578***	1.555859	22.880	12382
Teacher Collaboration	-0.450906	0.307624	-1.466	12382
Enrollment - Small	2.492043**	0.960553	2.594	12382
Enrollment - Large	-0.197778	1.364633	-0.145	12382
Time (Slope)	31.413783***	0.986897	31.831	872
Teacher Collaboration	1.050869***	0.188325	5.580	12382
Enrollment - Small	-1.741655***	0.424617	-4.102	12382
Enrollment - Large	0.782734**	0.301977	2.592	12382
Enrollment Small * Teacher Collaboration	-0.837768	0.460655	-1.819	12382
Enrollment Large * Teacher Collaboration	-0.001741	0.580383	-0.003	12382

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.14. Interaction of School Enrollment and School Climate - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.086582***	1.518622	23.763	12382
School Climate	1.063642*	0.487220	2.183	12382
Enrollment - Small	1.001506	2.203240	0.455	12382
Enrollment - Large	0.606888	1.932435	0.314	12382
Time (Slope)	31.356831***	0.984234	31.859	872
School Climate	-0.611590*	0.309065	-1.979	12382
Enrollment - Small	-1.830394***	0.416163	-4.398	12382
Enrollment - Large	0.764674**	0.302068	2.531	12382
Enrollment Small * School Climate	-0.033083	0.818251	-0.040	12382
Enrollment Large * School Climate	-0.304732	0.741646	-0.411	12382

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table A.15. Interaction of School Enrollment and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	25.381930***	1.153900	21.997	11993
Teacher Collaboration	-0.146345	0.230473	-0.635	11993
Enrollment - Small	3.133474***	0.764258	4.100	11993
Enrollment - Large	1.620907	0.951284	1.704	11993
Time (Slope)	24.872191***	0.763434	32.579	872
Teacher Collaboration	0.752933***	0.141493	5.321	11993
Enrollment - Small	-1.698518***	0.307188	-5.529	11993
Enrollment - Large	0.660890**	0.241663	2.735	11993

Table A.15. Interaction of School Enrollment and Teacher Collaboration – Mathematics—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Enrollment Small * Teacher Collaboration	-1.194998***	0.368428	-3.244	11993
Enrollment Large * Teacher Collaboration	-0.632306	0.399036	-1.585	11993

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.16. Interaction of School Enrollment and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.245941***	1.160482	22.616	11993
School Climate	0.730055*	0.368796	1.980	11993
Enrollment - Small	0.289375	1.544937	0.187	11993
Enrollment - Large	2.297519	1.663140	1.381	11993
Time (Slope)	24.827855***	0.765380	32.439	872
School Climate	-0.414933	0.237472	-1.747	11993
Enrollment - Small	-1.818265***	0.304133	-5.979	11993
Enrollment - Large	0.615224**	0.244037	2.521	11993
Enrollment Small * School Climate	0.214418	0.583380	0.368	11993
Enrollment Large * School Climate	-0.770962	0.621061	-1.241	11993

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.17. Interaction of School Minority Enrollment and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	35.982765***	1.754476	20.509	12382
Teacher Collaboration	-0.629308	0.485407	-1.296	12382
Minority Enrollment - Low	-0.531311	1.140281	-0.466	12382
Minority Enrollment - High	-0.998441	1.454593	-0.686	12382
Time (Slope)	31.376017***	0.985612	31.834	872
Teacher Collaboration	1.071475***	0.188396	5.687	12382
Minority Enrollment - Low	-0.413671	0.354407	-1.167	12382
Minority Enrollment - High	-0.012651	0.414842	-0.030	12382
Minority Enrollment Low * Teacher Collaboration	-0.100779	0.497214	-0.203	12382
Minority Enrollment High * Teacher Collaboration	0.206627	0.662464	0.312	12382

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.18. Interaction of School Minority Enrollment and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.240749***	0.825533	43.900	12382
School Climate	1.288407	0.716084	1.799	12382
Minority Enrollment - Low	0.062920	2.136166	0.029	12382

Table A.18. Interaction of School Minority Enrollment and School Climate – Reading—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Minority Enrollment - High	1.257098	2.514855	0.500	12382
Time (Slope)	25.956629***	0.626406	41.437	872
School Climate	-0.605751*	0.309018	-1.960	12382
Minority Enrollment - Low	-0.430013	0.351744	-1.223	12382
Minority Enrollment - High	-0.027103	0.418312	-0.065	12382
Minority Enrollment Low * School Climate	-0.297456	0.791328	-0.376	12382
Minority Enrollment High * School Climate	-0.708018	0.919020	-0.770	12382

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.19. Interaction of School Minority Enrollment and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	25.954420***	1.262327	20.561	11993
Teacher Collaboration	-0.421669	0.353663	-1.192	11993
Minority Enrollment - Low	1.165318	0.797890	1.460	11993
Minority Enrollment - High	-0.445749	0.895973	-0.498	11993
Time (Slope)	24.840742***	0.764391	32.497	872
Teacher Collaboration	0.774786***	0.141536	5.474	11993

Table A.19. Interaction of School Minority Enrollment and Teacher Collaboration – Mathematics—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Minority Enrollment - Low	-0.455226	0.279785	-1.627	11993
Minority Enrollment - High	-0.303288	0.319390	-0.950	11993
Minority Enrollment Low * Teacher Collaboration	-0.207917	0.367604	-0.566	11993
Minority Enrollment High * Teacher Collaboration	0.011130	0.430849	0.026	11993

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.20. Interaction of School Minority Enrollment and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	27.020421***	0.609688	44.318	11993
School Climate	0.788212	0.530272	1.486	11993
Minority Enrollment - Low	1.380243	1.558976	0.885	11993
Minority Enrollment - High	-0.144691	1.663993	-0.087	11993
Time (Slope)	20.553151***	0.493863	41.617	872
School Climate	-0.437306	0.237031	-1.845	11993
Minority Enrollment - Low	-0.481198	0.277567	-1.734	11993
Minority Enrollment - High	-0.310126	0.317666	-0.976	11993

Table A.20. Interaction of School Minority Enrollment and School Climate – Mathematics—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Minority Enrollment Low * School Climate	-0.236155	0.584022	-0.404	11993
Minority Enrollment High * School Climate	-0.108451	0.631990	-0.172	11993

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.21. Interaction of School FRPL and Teacher Collaboration - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	37.185044***	1.839148	20.219	12383
Teacher Collaboration	-0.909913**	0.346984	-2.622	12383
FRPL	-0.046931**	0.016544	-2.837	12383
Time (Slope)	31.428759***	0.987393	31.830	872
Teacher Collaboration	1.064622***	0.187356	5.682	12383
FRPL	-0.011529	0.006821	-1.690	12383
FRPL * Teacher Collaboration	0.007941	0.006906	1.150	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.22. Interaction of School FRPL and School Climate - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.085462***	1.518355	23.766	12383
School Climate	0.961014	0.549049	1.750	12383
FRPL	-0.032564	0.028292	-1.151	12383
Time (Slope)	31.357918***	0.984705	31.845	872
School Climate	-0.615325*	0.308035	-1.998	12383
FRPL	-0.011135	0.006833	-1.630	12383
FRPL * School Climate	0.000930	0.010125	0.092	12383

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.23. Interaction of School FRPL and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.457414***	1.471798	17.976	11994
Teacher Collaboration	-0.601404*	0.299933	-2.005	11994
FRPL	-0.024143*	0.012564	-1.922	11994
Time (Slope)	24.846412***	0.763474	32.544	872
Teacher Collaboration	0.777002***	0.140748	5.521	11994
FRPL	0.000727	0.005505	0.132	11994
FRPL * Teacher Collaboration	0.001537	0.005300	0.290	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.24. Interaction of School FRPL and School Climate - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.216379***	1.159400	22.612	11994
School Climate	0.848136	0.456476	1.858	11994
FRPL	-0.004751	0.020697	-0.230	11994
Time (Slope)	24.843839***	0.765416	32.458	872
School Climate	-0.424618	0.237349	-1.789	11994
FRPL	0.000578	0.005496	0.105	11994
FRPL * School Climate	-0.006075	0.007538	-0.806	11994

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.25. Interaction of School Type and Teacher Collaboration - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	35.981595***	1.535951	23.426	12384
Teacher Collaboration	-0.630780*	0.269471	-2.341	12384
School Type - Private	1.107674	1.116792	0.992	29013
Time (Slope)	31.370429***	0.984509	31.864	872
Teacher Collaboration	1.073399***	0.186868	5.744	12384
School Type - Private	-0.569423	0.493882	-1.153	872
School Type – Private * Teacher Collaboration	-0.213956	0.551688	-0.388	29013

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.26. Interaction of School Type and School Climate - Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	36.079695***	1.518194	23.765	12384
School Climate	0.962417*	0.396136	2.430	12384
School Type - Private	0.681437	0.580691	1.173	29013
Time (Slope)	31.359020***	0.984197	31.863	872
School Climate	-0.611233*	0.306138	-1.997	12384
School Type - Private	-0.578688	0.488285	-1.185	872
School Type – Private * School Climate	0.188008	0.930032	0.202	29013

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table A.27. Interaction of School Type and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	25.945965***	1.134065	22.879	11995
Teacher Collaboration	-0.430766*	0.195070	-2.208	11995
School Type - Private	2.415945**#	0.974736	2.479	28711
Time (Slope)	24.869310***	0.760573	32.698	872
Teacher Collaboration	0.765838***	0.139464	5.491	11995
School Type - Private	-0.729844	0.386716	-1.887	872
School Type – Private * Teacher Collaboration	-0.632809	0.531493	-1.191	28711

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

Table A.28. Interaction of School Type and School Climate - Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	26.236078***	1.159399	22.629	11995
School Climate	0.569066	0.307927	1.848	11995
School Type - Private	1.189805**#	0.480697	2.475	28711
Time (Slope)	24.832430***	0.764842	32.467	872
School Climate	-0.428699	0.236415	-1.813	11995
School Type - Private	-0.763238*	0.381387	-2.001	872
School Type – Private * School Climate	0.387512	0.828855	0.468	28711

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

APPENDIX B

CONFIRMATORY FACTOR ANALYSIS

Figures B.1, B.2, B.3, and B.4 show two- and three-factor models analyzed in AMOS. In all four of the models, the following variables are conceptualized as measuring teacher collaboration: LESSON PLANNING, the frequency with which teachers meet with other teachers to discuss lesson planning; DISCUSS CURRICULUM, meeting with other teachers to discuss curriculum development; DISCUSS CHILD, meeting with other teachers or specialists to discuss individual children; and SPED TEACHER, meeting with the special education teacher or service providers to discuss and plan for the children with disabilities in my class. The results from the CFA confirm those from the EFA in which these four variables clearly load together on one factor.

The difference between the two-factor models in Figures B.1 and B.2 and the three-factor models in Figures B.3 and B.4 is that the two-factor models include variables on principal leadership as part of the measure of overall school climate. These variables are ADMIN VISION, the school administrator knows what kind of school he/she wants and has communicated it to the staff; ADMIN PRESSURE, the school administrator deals effectively with pressures from outside the school (for example, budget, parents, school board) that might otherwise affect my teaching; ADMIN PRIORITIZES, the school administrator sets priorities, makes plans, and sees that they are carried out; and ADMIN ENCOURAGES, the school administration's behavior toward the staff is supportive and encouraging. In contrast, the three-factor models conceptualize these four variables as measuring a leadership construct that is distinct from the school climate construct.

Finally, in both the two-factor and three-factor models, variables with low factor loadings were removed from the model and the model was re-analyzed. Specifically, in Figures B.1 and B.3, two varables—CNTRLC and NOTCAP—both had factor loadings below .4 and were removed from subsequent analyses (e.g., Figures B.2 and B.4). Models were compared by reviewing the factor loadings, the root mean square error of approximation (RMSEA), and comparative fit index (CFI), and by conducting a chi-squared test.

It is important to determine which one of these models best fits the data to be sure the PLC constructs that will be included in the HCM analysis are valid and therefore measuring what we think they are measuring. For example, if leadership is a separate construct, but the variables that measure leadership are included among the variables that measure school climate, it could have an impact on whether we can adequately assess the effects of leadership and school climate, especially if they impact student achievement in different ways. Model fit statistics are presented in Table B.1. In all four models, the chi-square is significant, which indicates a lack of satisfactory fit between the models and the observed data. However, chi-square tends to be significant when sample sizes are large, as in the case of these analysis (n=15,819) (Schumacker & Lomax, 2004). An examination of the root mean square error of approximation (RMSEA) and the comparative fit index (CFI) indicates that the two-factor models, those without a separate leadership construct, demonstrate the poorest fit.

The results for the three-factor models are somewhat less clear. A value of less than or equal to .8 for RMSEA is considered adequate for model fit; both three-factor models meet this criterion. A value of at least .9 for CFI is considered good; model 4 meets that criterion while model 3 is very close. A chi-square difference test between the two models indicates that model 4 is significantly different from model 3 and a better fit of the data. As a result, model 4 was selected for this study. With three of the initial 17 variables excluded from the model, teachers who had responded to at least half of the remaining PLC-related questionnaire items were included in the analysis.

Figure B.1. Model 1: Sixteen Variable Two-Factor Model

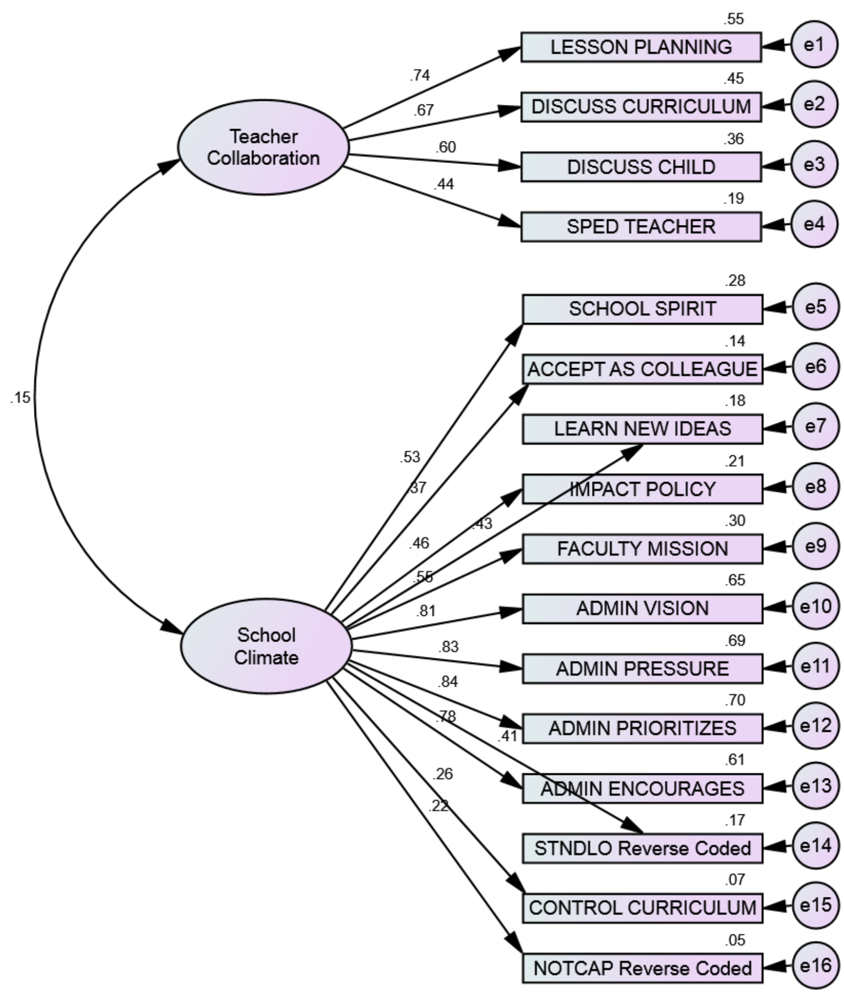


Figure B.2. Model 2: Fourteen Variable Two-Factor Model

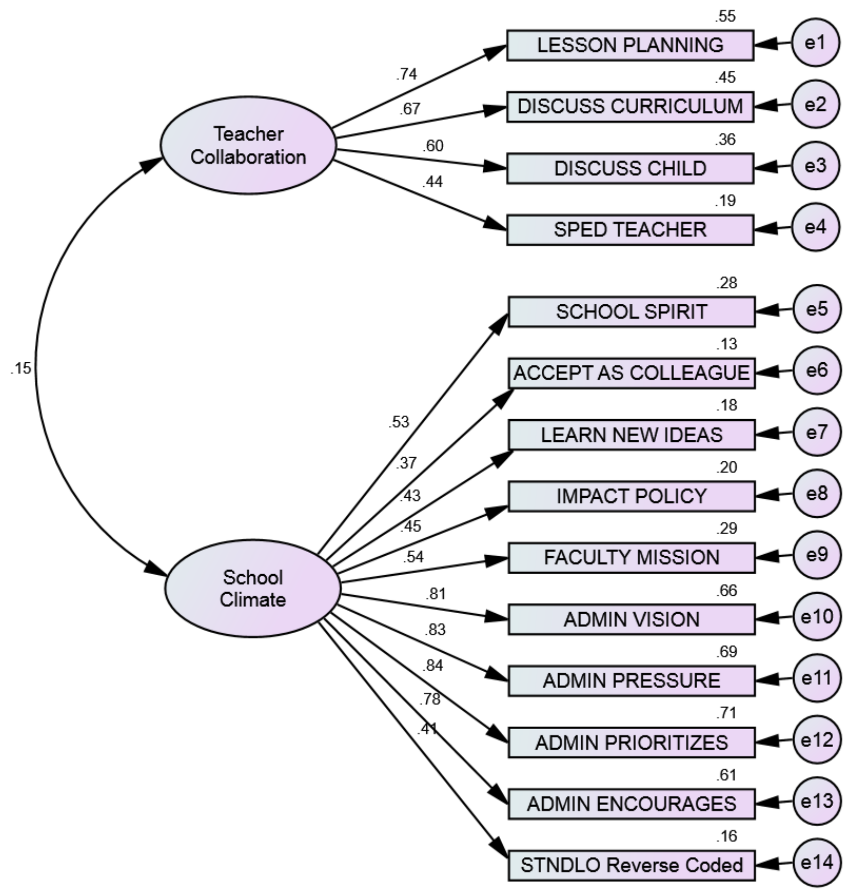


Figure B.3. Model 3: Sixteen Variable Three-Factor Model

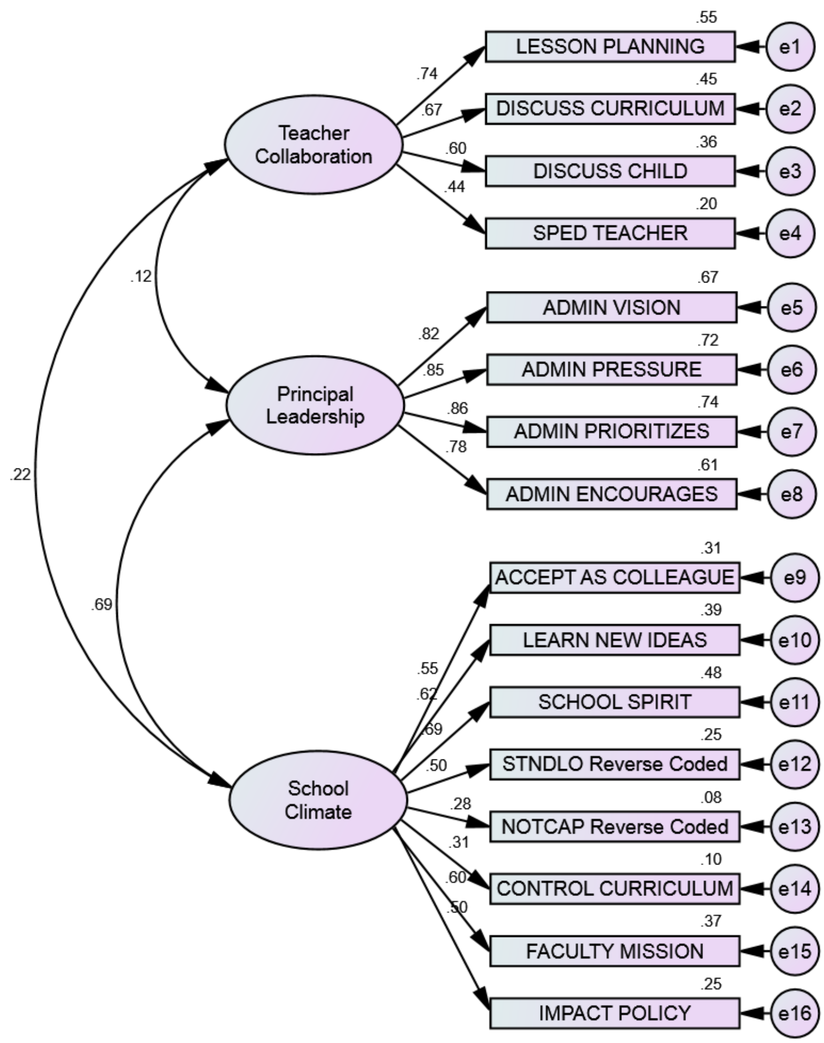


Figure B.4. Model 4: Fourteen Variable Three-Factor Model

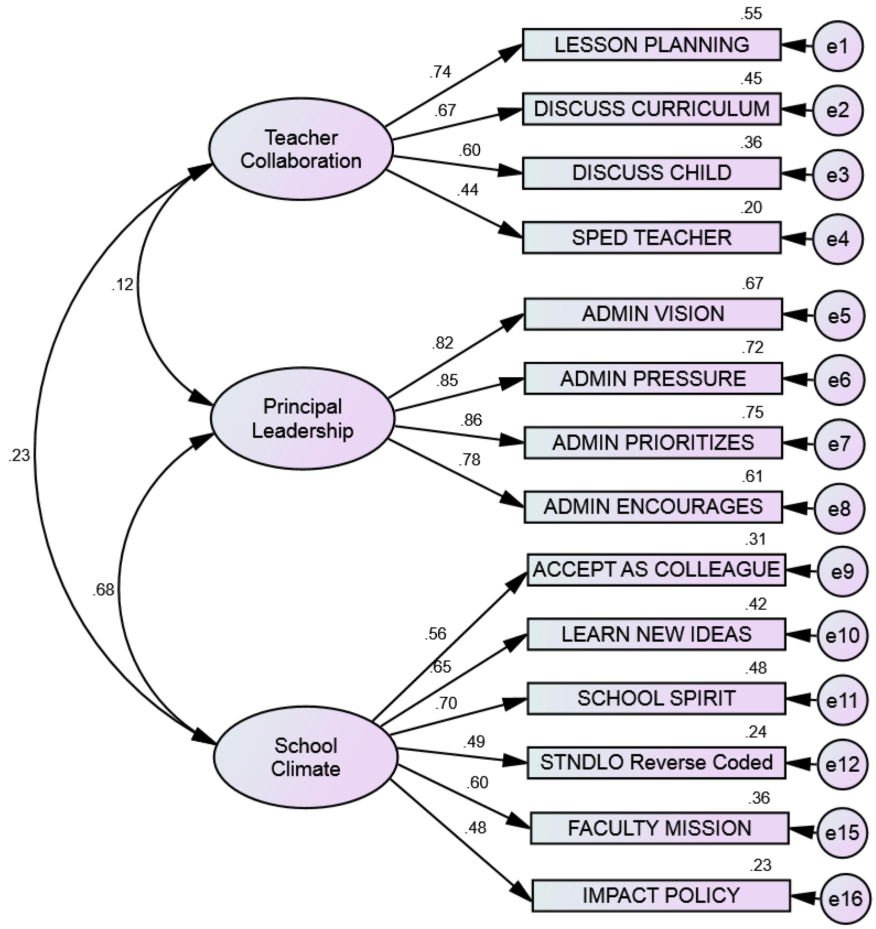


Table B.1. Model Fit Comparisons

	Model 1	Model 2	Model 3	Model 4
RMSEA	.098	.105	.074	.078
CFI	.813	.832	.893	.910
X^2 (DF), P-Value	15,665 (103), .000	13,404 (76), .000	8,949 (101), .000	7,207 (74), .000

As noted above, the three constructs derived from factor analysis are teacher collaboration, principal leadership, and school climate. Each of these constructs and the individual items they comprise are described in more detail below.

Teacher Collaboration. Four items comprise the teacher collaboration construct used in this study: how frequently teachers meet with 1) other teachers to discuss lesson planning; 2) other teachers to discuss curriculum development; 3) other teachers or specialists to discuss individual children; and 4) the special education teacher or service providers to discuss and plan for the children with disabilities in their class. These items reflect the extent to which teachers communicate with each other about practice, pedagogy, and their students, as well as their participation in collaborative activities such as lesson planning.

Teacher collaboration is an essential element of PLCs. It provides a critical vehicle for overcoming teacher isolation and providing teachers with a network of support and expertise. Researchers posit that providing teachers with access to the support and expertise of their colleagues promotes instructional improvement and therefore improved student achievement. Studies by Goddard, Goddard, and Tschannen-Moran (2007) and Ronfeldt, Farmer, McQueen, and Grissom (2015) have demonstrated a significant and positive relationship between teacher collaboration and student achievement in reading and mathematics.

Principal Leadership. Four items comprise the school leadership factor: the extent to which teachers agree or disagree that the school administrator 1) knows what kind of school he/she wants and has communicated it to the staff; 2) deals effectively with pressures from outside the school (for example, budget, parents, school board) that might otherwise affect my teaching; 3) sets priorities, makes plans, and sees that they are carried out; and 4) the school administration's behavior toward the staff is supportive and encouraging. Together, these items reflect the extent to which teachers perceive principal leadership to be effective and supportive.

While some researchers view school and departmental leadership as a facilitator of PLCs, others, like Visscher and Witziers (2004), include it as a key element of PLCs themselves. As described above, the questionnaire items that comprise the principal leadership construct in this study reflect the PLC elements of shared vision and practices. The importance of supportive leadership is demonstrated in the national survey of teachers sponsored by Scholastic and the Gates Foundation. This study found that supportive leadership, along with time for collaboration with colleagues, was a more important factor in teachers' job satisfaction and retention than higher salaries (2012).

School Climate. Six items comprise the school climate factor. The first five variables represent the extent to which teachers agree or disagree that 1) staff members in the school generally have school spirit; 2) the teacher feels accepted as a colleague by most staff members; 3) teachers in the school are continually learning and seeking new ideas; 4) there is broad agreement among the entire school faculty about the central mission of the school; and 5) the academic standards at this school are too low. This last variable was reverse coded. The sixth variable gauged how much influence teachers think teachers in the school have over school policy in areas such as determining discipline policy, deciding how some school funds will be spent, and assigning children to classes.

The school climate construct, unlike the teacher collaboration and principal leadership construct, reflects a wider array of PLC dimensions. The first, second, and third items reflect research that suggests social and human resources such as trust, respect, and openness to learning (in contrast to structural resources) are conducive to PLCs. The third item also reflects PLCs' focus on ongoing teacher learning. The fourth item suggests the existence of a core set of shared values among staff, a foundational feature of PLCs. The fifth item is indicative of an environment wherein shared decision making is valued. The sixth and final item reflects a focus on student learning and the belief that all students can learn.

Hierarchical Cross-Classified Modeling

The following hierarchical cross-classified model was used to analyze the effects of the PLC and other salient variables on students' reading performance. The same model was used to analyze the effects of the PLC variables on students' mathematics performance with the mathematics IRT scale score as the outcome variable. Data were weighted and continuous variables were centered on the grand mean. Cumulative effects models were used to account for the carryover of treatment effects across years. The results of these models are presented in tables B.2 to B.17.

$$
\begin{aligned}
RSCORE_{ijkl} = {} & \delta_{000} + \delta_{001}\text{*SCTYP\_PR}_{kl} + \delta_{010}\text{*GENDER\_M}_{jl} + \delta_{020}\text{*AVESES}_{jl} \\
& + \delta_{030}\text{*ATRISK\_R}_{jl} + \delta_{040}\text{*RACE\_BHO}_{jl} + \delta_{050}\text{*HGHSTD\_A}_{jl} + \delta_{060}\text{*AVESAT}_{jl} \\
& + \delta_{070}\text{*PLC\_TC}_{jl} + \delta_{080}\text{*PLC\_PL}_{jl} + \delta_{090}\text{*PLC\_SC}_{jl} + \delta_{0100}\text{*ENRL\_S}_{jl}
\end{aligned}
$$

$+ \delta_{0110}$*ENRL_L$_{jl}$ + δ_{0120}*MIN_L$_{jl}$ + δ_{0130}*MIN_H$_{jl}$ + δ_{0140}*SUMFRPL$_{jl}$

$+ \delta_{100}$*$TIME\_R_{ijkl}$ + δ_{101}*$TIME\_R_{ijkl}$*SCTYP_PR$_{kl}$ + δ_{110}*$TIME\_R_{ijkl}$*GENDER_M$_{jl}$ + δ_{120}*$TIME\_R_{ijkl}$*AVESES$_{jl}$

$+ \delta_{130}$*$TIME\_R_{ijkl}$*ATRISK_R$_{jl}$ + δ_{140}*$TIME\_R_{ijkl}$*RACE_BHO$_{jl}$ + δ_{150}*$TIME\_R_{ijkl}$*HGHSTD_A$_{jl}$ + δ_{160}*$TIME\_R_{ijkl}$*AVESAT$_{jl}$ + δ_{170}*$TIME\_R_{ijkl}$*PLC_TC$_{jl}$ + δ_{180}*$TIME\_R_{ijkl}$*PLC_PL$_{jl}$ + δ_{190}*$TIME\_R_{ijkl}$*PLC_SC$_{jl}$ + δ_{1100}*$TIME\_R_{ijkl}$*ENRL_S$_{jl}$ + δ_{1110}*$TIME\_R_{ijkl}$*ENRL_L$_{jl}$ + δ_{1120}*$TIME\_R_{ijkl}$*MIN_L$_{jl}$ + δ_{1130}*$TIME\_R_{ijkl}$*MIN_H$_{jl}$ + δ_{1140}*$TIME\_R_{ijkl}$*SUMFRPL$_{jl}$ + b_{10jl}*$TIME\_R_{ijkl}$ + c_{10kl}*$TIME\_R_{ijkl}$ + d_{10l}*$TIME\_R_{ijkl}$ + e_{ijkl}

Table B.2 Effects of PLCs on Student Reading Performance

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.954795***	1.478903	22.283	8357
Gender – Male	-1.181409***	0.299399	-3.946	8357
Race – Black, Hispanic, Other	-0.670510	0.416017	-1.612	8357
SES	2.924599***	0.293281	9.972	8357
At-Risk Status	-7.274513***	0.309117	-23.533	8357
Teacher Advanced Degree	-0.589988	0.339137	-1.740	8357
Teacher Job Satisfaction	0.222128	0.293601	0.757	8357
Teacher Collaboration	-0.422447	0.325273	-1.299	8357
Principal Leadership	0.611884*	0.267794	2.285	8357
School Climate	-0.179360	0.560673	-0.320	8357
School Enrollment - Small	1.064143**	0.433157	2.457	8357

Table B.2 Effects of PLCs on Student Reading Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
School Enrollment - Large	-0.016189	0.450841	-0.036	8357
Minority Enrollment - Low	-0.461136	0.458864	-1.005	8357
Minority Enrollment - High	-1.583325**	0.579688	-2.731	8357
School FRPL	-0.009074	0.007677	-1.182	8357
School Type – Private	-1.132840	1.816894	-0.624	22157
Time (Slope)	35.794485***	0.924535	38.716	694
Gender – Male	-0.449377**	0.181128	-2.481	8357
SES	0.857952***	0.159193	5.389	8357
Race – Black, Hispanic, Other	-0.516204*	0.258909	-1.994	8357
At-Risk Status	-7.391700***	0.239875	-30.815	8357
Teacher Advanced Degree	-0.678394**	0.242151	-2.802	8357
Teacher Job Satisfaction	-1.244731***	0.186854	-6.662	8357
Teacher Collaboration	0.982965***	0.244172	4.026	8357
Principal Leadership	-0.300002	0.202262	-1.483	8357
School Climate	-0.196583	0.418552	-0.470	8357
School Enrollment - Small	-1.048736*	0.527289	-1.989	8357
School Enrollment - Large	-0.678366	0.456584	-1.486	8357

Table B.2 Effects of PLCs on Student Reading Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
School Minority Enrollment – Low	-1.503428***	0.439029	-3.424	8357
School Minority Enrollment - High	1.448086**	0.474483	3.052	8357
School FRPL	-0.042830***	0.008167	-5.244	8357
School Type - Private	-1.388058	1.946374	-0.713	694

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.3 Effects of PLCs on Student Mathematics Performance

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.165944***	1.135866	21.275	8243
Gender – Male	-0.413717	0.224714	-1.841	8243
Race – Black, Hispanic, Other	-1.064264***	0.320394	-3.322	8243
SES	2.821304***	0.208699	13.519	8243
At-Risk Status	-7.301237***	0.222824	-32.767	8243
Teacher Advanced Degree	-0.165309	0.254178	-0.650	8243
Teacher Job Satisfaction	0.197231	0.226230	0.872	8243
Teacher Collaboration	-0.458637	0.241716	-1.897	8243
Principal Leadership	0.212912	0.213838	0.996	8243
School Climate	0.364281	0.486410	0.749	8243
School Enrollment - Small	1.023230**	0.317669	3.221	8243

Table B.3 Effects of PLCs on Student Mathematics Performance—Continued

Fixed effects	Coefficient	SE	*t*-ratio	df
School Enrollment - Large	0.457347	0.339546	1.347	8243
Minority Enrollment - Low	1.156774**	0.365006	3.169	8243
Minority Enrollment - High	-1.147980**	0.398620	-2.880	8243
School FRPL	-0.006795	0.006254	-1.086	8243
School Type Private	-1.964380	2.568723	-0.765	22127
Time (Slope)	28.145003***	0.732403	38.428	694
Gender – Male	1.199378***	0.140098	8.561	8243
SES	0.580387***	0.133628	4.343	8243
Race – Black, Hispanic, Other	-0.567497**	0.217715	-2.607	8243
At-Risk Status	-7.169497***	0.183133	-39.149	8243
Teacher Advanced Degree	-0.547283**	0.183214	-2.987	8243
Teacher Job Satisfaction	-0.950286***	0.146743	-6.476	8243
Teacher Collaboration	0.897876***	0.184402	4.869	8243
Principal Leadership	-0.074785	0.159949	-0.468	8243
School Climate	-0.582505	0.351681	-1.656	8243
School Enrollment - Small	-1.053075*	0.433121	-2.431	8243
School Enrollment - Large	-0.557362	0.355944	-1.566	8243
School Minority Enrollment - Low	-1.724000***	0.341702	-5.045	8243

Table B.3 Effects of PLCs on Student Mathematics Performance—Continued

Fixed effects	Coefficient	SE	t-ratio	df
School Minority Enrollment - High	0.989760**	0.394012	2.512	8243
School FRPL	-0.025019***	0.006935	-3.608	8243
School Type - Private	-2.321428	2.638561	-0.880	694

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

Table B.4. Interaction of Race and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	32.948116***	1.478136	32.974924***	1.480959	32.999391***	1.483883
PLC	-0.455120	0.361436	0.462792	0.300951	-0.338727	0.607627
Race – Black, Hispanic, Other	-0.657559	0.417700	-0.716687	0.419088	-0.707686	0.421764
Time (Slope)	35.796846***	0.924419	35.783949***	0.924999	35.777283***	0.926676
PLC	0.981616***	0.244427	-0.312291	0.202449	-0.210829	0.419774
Race – Black, Hispanic, Other	-0.522441**	0.261404	-0.504554**	0.259666	-0.507022**	0.260238
Race – Black, Hispanic, Other * PLC	0.108042	0.447795	0.488820	0.370460	0.503526	0.746506

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.5. Interaction of Race and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	24.162704***	1.134638	24.159279***	1.136044	24.156395***	1.138171
PLC	-0.472431	0.278937	0.273453	0.233057	0.403762	0.536601
Race – Black, Hispanic, Other	-1.059487	0.325723	-1.046684***	0.319893	-1.055749***	0.322266
Time (Slope)	28.146154***	0.732598	28.147525***	0.732579	28.148533***	0.734062
PLC	0.897750***	0.184450	-0.072346	0.160164	-0.580962	0.352015
Race – Black, Hispanic, Other	0.041425**	0.340937	-0.572489**	0.217807	-0.569778**	0.217774
Race – Black, Hispanic, Other * PLC	0.041425	0.340937	-0.178379	0.256553	-0.107639	0.534606

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.6. Interaction of SES and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	33.031500***	1.474541	33.042210***	1.478681	33.063902***	1.478361
PLC	-0.419394	0.323884	0.604473*	0.268864	-0.202727	0.563524
SES	2.912353***	0.291217	2.944421***	0.291621	2.962787***	0.295629
Time (Slope)	35.814465***	0.924673	35.808591***	0.924822	35.802304***	0.924674
PLC	0.981093***	0.244545	-0.300496	0.202287	-0.201749	0.418789
SES	0.864198***	0.160602	0.852967***	0.158530	0.848551***	0.158142
SES * PLC	-0.101008	0.326622	-0.166464	0.252870	-0.395373	0.497625

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.7. Interaction of SES and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	24.262716***	1.137213	24.214152***	1.134862	24.221589***	1.134535
PLC	-0.459103	0.240750	0.218359	0.216776	0.333169	0.493717
SES	2.850758***	0.209776	2.811612***	0.208122	2.847995***	0.212839
Time (Slope)	28.143573***	0.733824	28.159837***	0.731782	28.156959***	0.731748
PLC	0.898385***	0.184137	-0.075570	0.159947	-0.579768	0.351308
SES	0.564665***	0.133410	0.583582***	0.133851	0.572890***	0.134073
SES * PLC	0.245836	0.241476	0.077458	0.192414	-0.274413	0.360717

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.8. Interaction of At-Risk Status and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	32.993982***	1.484608	32.959729***	1.479150	32.941564***	1.478327
PLC	-0.345770	0.354058	0.674775*	0.295288	-0.058713	0.602694
At Risk	-7.336220***	0.308573	-7.269521***	0.307775	-7.255073***	0.308406
Time (Slope)	35.776111***	0.925985	35.793597***	0.924479	35.800515***	0.924203
PLC	0.987764***	0.244160	-0.298699	0.202416	-0.186397	0.419620
At Risk	-7.372795***	0.239595	-7.399007***	0.239941	-7.406397***	0.239740
At Risk * PLC	-0.425099	0.415798	-0.302300	0.341473	-0.608894	0.689471

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.9. Interaction of At-Risk Status and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	24.276984***	1.138588	24.175717***	1.136745	24.150771***	1.137058
PLC	-0.265370	0.261034	0.271137	0.231913	0.655096	0.517734
At Risk	-7.445311***	0.229060	-7.295366***	0.222750	-7.247835***	0.221292
Time (Slope)	28.106184***	0.734031	28.142584***	0.732389	28.158717***	0.733059
PLC	0.899786***	0.184357	-0.075798	0.159978	-0.571959	0.352034
At Risk	-7.125467***	0.182818	-7.175086***	0.183488	-7.202905***	0.184122
At Risk * PLC	-0.972962***	0.275112	-0.246679	0.220434	-1.336900**	0.466758

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.10. Interaction of School Enrollment and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	32.884557***	1.483202	33.014062	1.481941	32.937723***	1.339173
Enrollment - Small	1.693117	1.245949	3.014801	2.174758	0.928352	2.439335
Enrollment - Large	-0.508106	1.254855	1.926613	1.548435	-0.923836	2.211797
PLC	-0.397900	0.377641	0.862930**	0.314949	-0.266910	0.724074
Time (Slope)	35.789718***	0.924840	35.761503***	0.925052	35.802489***	0.926140
Enrollment - Small	-1.006036	0.535267	-1.065799**	0.528489	-1.045375**	0.529450
Enrollment - Large	-0.674363	0.456021	-0.690208	0.456868	-0.667977	0.461110
PLC	0.971600***	0.245169	-0.319996	0.203549	-0.198964	0.418033
Enrollment Small * PLC	-0.387685	0.691065	-0.597313	0.652168	0.054122	1.021488
Enrollment Large * PLC	0.260179	0.642337	-0.589354	0.445131	0.388905	0.928665

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.11. Interaction of School Enrollment and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	24.057291***	1.136054	24.147704***	1.136983	24.153788***	1.137628
Enrollment - Small	-0.248607	0.271914	0.184162	0.249269	0.268191	0.594536
Enrollment - Large	2.394502**	0.839038	0.043007	1.172294	1.197182	1.861943
PLC	1.186013	0.869546	0.982378	1.304985	-0.740501	1.812972
Time (Slope)	28.112552***	0.733287	28.151068***	0.732939	28.151712***	0.733494
Enrollment - Small	0.890711***	0.184889	-0.064642	0.159513	-0.588725	0.357155
Enrollment - Large	-0.978615*	0.436269	-1.050137*	0.431576	-1.050321*	0.434060
PLC	-0.550274	0.356686	-0.556777	0.357269	-0.545804	0.358227
Enrollment Small * PLC	-0.817026	0.467578	0.307847	0.353750	-0.079368	0.782599
Enrollment Large * PLC	-0.389089	0.438237	-0.163454	0.370243	0.517124	0.751374

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.12. Interaction of School Minority Enrollment and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	32.973508***	1.479894	32.924952***	1.479665	32.944312***	1.478928
PLC	-0.273263	0.627857	0.750809	0.458453	0.097595	1.008027
Minority Enrollment - Low	-0.147793	1.237587	0.389169	1.744530	0.221889	2.578330
Minority Enrollment - High	-1.059860	1.563578	-1.959662	2.130021	-0.249369	2.885405
Time (Slope)	35.787463***	0.925246	35.799756***	0.925073	35.795970***	0.923447
PLC	0.983926***	0.247329	-0.316361	0.204783	-0.193891	0.422654
Minority Enrollment - Low	-1.490261***	0.444518	-1.510621***	0.439229	-1.506675***	0.439556
Minority Enrollment - High	1.462025**	0.474807	1.448163**	0.477148	1.435283**	0.478212
Minority Enrollment - Low * PLC	-0.175921	0.644657	-0.253527	0.512548	-0.288684	1.059163
Minority Enrollment – High * PLC	-0.294220	0.802141	0.121489	0.600924	-0.576872	1.190030

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.13. Interaction of School Minority Enrollment and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	24.193149***	1.139944	24.146715***	1.134332	24.187090***	1.135942
PLC	-0.321122	0.415923	0.318780	0.334416	0.088161	0.795697
Minority Enrollment - Low	1.378688	0.847247	1.761915	1.211810	0.666117	1.974848
Minority Enrollment - High	-0.445795	0.870983	-1.120395	1.329617	-2.715650	1.958387
Time (Slope)	28.134865***	0.733138	28.147733***	0.732662	28.138411***	0.732985
PLC	0.901809***	0.185115	-0.080651	0.160566	-0.582475	0.352301
Minority Enrollment - Low	-1.714521***	0.345032	-1.728517***	0.342361	-1.723012***	0.342508
Minority Enrollment - High	1.006661**	0.397364	0.986509**	0.393661	1.004054**	0.393655
Minority Enrollment - Low * PLC	-0.126060	0.437898	-0.180763	0.353306	0.208786	0.816058
Minority Enrollment – High * PLC	-0.397063	0.472381	-0.003981	0.397090	0.681846	0.831079

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.14. Interaction of School FRPL and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	32.888243***	1.484080	32.965598***	1.480659	32.891633***	1.480847
PLC	-0.574731	0.460223	0.272055	0.382050	0.407970	0.813795
FRPL	-0.016553	0.016140	-0.036797	0.022707	0.024623	0.031175
Time (Slope)	35.814296***	0.926874	35.787744***	0.924880	35.828148***	0.924817
PLC	0.980917***	0.244679	-0.301289	0.201455	-0.189055	0.418145
FRPL	-0.042957***	0.008190	-0.042397***	0.008175	-0.043467***	0.008243
FRPL * PLC	0.004127	0.008300	0.008338	0.006292	-0.014175	0.012445

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.15. Interaction of School FRPL and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	24.230516***	1.141781	24.173389***	1.135364	24.116667***	1.140222
PLC	-0.305499	0.338832	0.344101	0.296554	0.835362	0.671960
FRPL	0.000349	0.011668	0.003511	0.016443	0.018480	0.020972
Time (Slope)	28.125663***	0.734168	28.142374***	0.732424	28.171541***	0.734202
PLC	0.897984***	0.184180	-0.075509	0.160083	-0.585312	0.352031
FRPL	-0.024895***	0.006954	-0.025162***	0.006934	-0.025458***	0.006945
FRPL * PLC	-0.003959	0.005793	-0.003113	0.004654	-0.010692	0.008653

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.16. Interaction of School Type and PLC Variables – Reading

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	32.975653***	1.478469	32.955674***	1.478734	32.975143***	1.478911
PLC	-0.391730	0.328399	0.611629*	0.267831	-0.147178	0.561772
School Type - Private	-1.441126	1.024019	-1.161015	1.902858	-1.283114	1.545381
Time (Slope)	35.788442***	0.924507	35.793691***	0.924254	35.799956***	0.923742
PLC	0.974606***	0.244611	-0.300469	0.202242	-0.198334	0.418697
School Type - Private	-1.448072	1.793685	-1.375282	1.885652	-1.201756	1.602040
School Type – Private * PLC	-2.332943**	0.736674	0.463904	4.005321	-7.900808	4.997288

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table B.17. Interaction of School Type and PLC Variables – Mathematics

Fixed effects	Model 1: Teacher Collaboration		Model 2: Principal Leadership		Model 3: School Climate	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	24.177845***	1.135759	24.159712***	1.135947	24.185168***	1.136108
PLC	-0.442813	0.243596	0.214143	0.213923	0.396277	0.487126
School Type - Private	-2.156723	2.023358	-1.812037	2.592923	-2.090281	2.277552
Time (Slope)	28.140861***	0.732392	28.149027***	0.732387	28.151954***	0.732059
PLC	0.893591***	0.184583	-0.072633	0.160076	-8.691035***	2.480101
School Type - Private	-2.325381	2.548377	-2.393754	2.480859	-2.142885	2.217287
School Type – Private * PLC	-1.201647	1.293416	-1.934921***	0.609134	-0.583143	0.351831

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

APPENDIX C

DETAILED HCM TABLES FROM CFA

Table C.1. Interaction of Race and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.948116***	1.478136	22.290	8356
Teacher Collaboration	-0.455120	0.361436	-1.259	8356
Race – Black, Hispanic, Other	-0.657559	0.417700	-1.574	8356
Time (Slope)	35.796846***	0.924419	38.724	694
Teacher Collaboration	0.981616***	0.244427	4.016	8356
Race – Black, Hispanic, Other	-0.522441*	0.261404	-1.999	8356
Race – Black, Hispanic, Other * Teacher Collaboration	0.108042	0.447795	0.241	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.2. Interaction of Race and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.974924***	1.480959	22.266	8356
Principal Leadership	0.462792	0.300951	1.538	8356
Race – Black, Hispanic, Other	-0.716687	0.419088	-1.710	8356
Time (Slope)	35.783949***	0.924999	38.685	694
Principal Leadership	-0.312291	0.202449	-1.543	8356
Race – Black, Hispanic, Other	-0.504554*	0.259666	-1.943	8356

Table C.2. Interaction of Race and Principal Leadership – Reading—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Race – Black, Hispanic, Other * Principal Leadership	0.488820	0.370460	1.319	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.3. Interaction of Race and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.999391***	1.483883	22.239	8356
School Climate	-0.338727	0.607627	-0.557	8356
Race – Black, Hispanic, Other	-0.707686	0.421764	-1.678	8356
Time (Slope)	35.777283***	0.926676	38.608	694
School Climate	-0.210829	0.419774	-0.502	8356
Race – Black, Hispanic, Other	-0.507022*	0.260238	-1.948	8356
Race – Black, Hispanic, Other * School Climate	0.503526	0.746506	0.675	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.4. Interaction of Race and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.162704***	1.134638	21.296	8242
Teacher Collaboration	-0.472431	0.278937	-1.694	8242
Race – Black, Hispanic, Other	-1.059487**	0.325723	-3.253	8242
Time (Slope)	28.146154***	0.732598	38.420	694
Teacher Collaboration	0.897750***	0.184450	4.867	8242
Race – Black, Hispanic, Other	-0.569833**	0.221006	-2.578	8242
Race – Black, Hispanic, Other * Teacher Collaboration	0.041425	0.340937	0.122	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.5. Interaction of Race and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.159279***	1.136044	21.266	8242
Principal Leadership	0.273453	0.233057	1.173	8242
Race – Black, Hispanic, Other	-1.046684***	0.319893	-3.272	8242
Time (Slope)	28.147525***	0.732579	38.423	694
Principal Leadership	-0.072346	0.160164	-0.452	8242
Race – Black, Hispanic, Other	-0.572489**	0.217807	-2.628	8242

Table C.5. Interaction of Race and Principal Leadership – Mathematics—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Race – Black, Hispanic, Other * Principal Leadership	-0.178379	0.256553	-0.695	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.6. Interaction of Race and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.156395***	1.138171	21.224	8242
School Climate	0.403762	0.536601	0.752	8242
Race – Black, Hispanic, Other	-1.055749***	0.322266	-3.276	8242
Time (Slope)	28.148533***	0.734062	38.346	694
School Climate	-0.580962	0.352015	-1.650	8242
Race – Black, Hispanic, Other	-0.569778**	0.217774	-2.616	8242
Race – Black, Hispanic, Other * School Climate	-0.107639	0.534606	-0.201	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.7. Interaction of SES and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	33.031500***	1.474541	22.401	8356
Teacher Collaboration	-0.419394	0.323884	-1.295	8356
SES	2.912353***	0.291217	10.001	8356
Time (Slope)	35.814465***	0.924673	38.732	694
Teacher Collaboration	0.981093***	0.244545	4.012	8356
SES	0.864198***	0.160602	5.381	8356
SES * Teacher Collaboration	-0.101008	0.326622	-0.309	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.8. Interaction of SES and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	33.042210***	1.478681	22.346	8356
Principal Leadership	0.604473*	0.268864	2.248	8356
SES	2.944421***	0.291621	10.097	8356
Time (Slope)	35.808591***	0.924822	38.719	694
Principal Leadership	-0.300496	0.202287	-1.485	8356
SES	0.852967***	0.158530	5.380	8356
SES * Principal Leadership	-0.166464	0.252870	-0.658	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.9. Interaction of SES and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	33.063902***	1.478361	22.365	8356
School Climate	-0.202727	0.563524	-0.360	8356
SES	2.962787***	0.295629	10.022	8356
Time (Slope)	35.802304***	0.924674	38.719	694
School Climate	-0.201749	0.418789	-0.482	8356
SES	0.848551***	0.158142	5.366	8356
SES * School Climate	-0.395373	0.497625	-0.795	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.10. Interaction of SES and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.262716***	1.137213	21.335	8242
Teacher Collaboration	-0.459103	0.240750	-1.907	8242
SES	2.850758***	0.209776	13.590	8242
Time (Slope)	28.143573***	0.733824	38.352	694
Teacher Collaboration	0.898385***	0.184137	4.879	8242
SES	0.564665***	0.133410	4.233	8242
SES * Teacher Collaboration	0.245836	0.241476	1.018	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.11. Interaction of SES and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.214152***	1.134862	21.337	8242
Principal Leadership	0.218359	0.216776	1.007	8242
SES	2.811612***	0.208122	13.509	8242
Time (Slope)	28.159837***	0.731782	38.481	694
Principal Leadership	-0.075570	0.159947	-0.472	8242
SES	0.583582***	0.133851	4.360	8242
SES * Principal Leadership	0.077458	0.192414	0.403	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.12. Interaction of SES and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.221589***	1.134535	21.349	8242
School Climate	0.333169	0.493717	0.675	8242
SES	2.847995***	0.212839	13.381	8242
Time (Slope)	28.156959***	0.731748	38.479	694
School Climate	-0.579768	0.351308	-1.650	8242
SES	0.572890***	0.134073	4.273	8242
SES * School Climate	-0.274413	0.360717	-0.761	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.13. Interaction of At-Risk Status and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.993982***	1.484608	22.224	8356
Teacher Collaboration	-0.345770	0.354058	-0.977	8356
At Risk	-7.336220***	0.308573	-23.775	8356
Time (Slope)	35.776111***	0.925985	38.636	694
Teacher Collaboration	0.987764***	0.244160	4.046	8356
At Risk	-7.372795***	0.239595	-30.772	8356
At Risk * Teacher Collaboration	-0.425099	0.415798	-1.022	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.14. Interaction of At-Risk Status and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.959729***	1.479150	22.283	8356
Principal Leadership	0.674775*	0.295288	2.285	8356
At Risk	-7.269521***	0.307775	-23.620	8356
Time (Slope)	35.793597***	0.924479	38.718	694
Principal Leadership	-0.298699	0.202416	-1.476	8356
At Risk	-7.399007***	0.239941	-30.837	8356
At Risk * Principal Leadership	-0.302300	0.341473	-0.885	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.15. Interaction of At-Risk Status and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.941564***	1.478327	22.283	8356
School Climate	-0.058713	0.602694	-0.097	8356
At Risk	-7.255073***	0.308406	-23.524	8356
Time (Slope)	35.800515***	0.924203	38.737	694
School Climate	-0.186397	0.419620	-0.444	8356
At Risk	-7.406397***	0.239740	-30.893	8356
At Risk * School Climate	-0.608894	0.689471	-0.883	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.16. Interaction of At-Risk Status and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.276984***	1.138588	21.322	8242
Teacher Collaboration	-0.265370	0.261034	-1.017	8242
At Risk	-7.445311***	0.229060	-32.504	8242
Time (Slope)	28.106184***	0.734031	38.290	694
Teacher Collaboration	0.899786***	0.184357	4.881	8242
At Risk	-7.125467***	0.182818	-38.976	8242
At Risk * Teacher Collaboration	-0.972962***	0.275112	-3.537	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.17. Interaction of At-Risk Status and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.175717***	1.136745	21.267	8242
Principal Leadership	0.271137	0.231913	1.169	8242
At Risk	-7.295366***	0.222750	-32.751	8242
Time (Slope)	28.142584***	0.732389	38.426	694
Principal Leadership	-0.075798	0.159978	-0.474	8242
At Risk	-7.175086***	0.183488	-39.104	8242
At Risk * Principal Leadership	-0.246679	0.220434	-1.119	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.18. Interaction of At-Risk Status and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.150771***	1.137058	21.240	8242
School Climate	0.655096	0.517734	1.265	8242
At Risk	-7.247835***	0.221292	-32.752	8242
Time (Slope)	28.158717***	0.733059	38.413	694
School Climate	-0.571959	0.352034	-1.625	8242
At Risk	-7.202905***	0.184122	-39.120	8242
At Risk * School Climate	-1.336900**	0.466758	-2.864	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.19. Interaction of School Enrollment and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.884557***	1.483202	22.171	8355
Teacher Collaboration	-0.397900	0.377641	-1.054	8355
Enrollment - Small	1.693117	1.245949	1.359	8355
Enrollment - Large	-0.508106	1.254855	-0.405	8355
Time (Slope)	35.789718***	0.924840	38.698	694
Teacher Collaboration	0.971600***	0.245169	3.963	8355
Enrollment - Small	-1.006036	0.535267	-1.880	8355
Enrollment - Large	-0.674363	0.456021	-1.479	8355
Enrollment Small * Teacher Collaboration	-0.387685	0.691065	-0.561	8355
Enrollment Large * Teacher Collaboration	0.260179	0.642337	0.405	8355

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.20. Interaction of School Enrollment and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	33.014062***	1.481941	22.278	8355
Principal Leadership	0.862930**	0.314949	2.740	8355
Enrollment - Small	-0.597313	0.652168	-0.916	8355
Enrollment - Large	-0.589354	0.445131	-1.324	8355
Time (Slope)	35.761503***	0.925052	38.659	694
Principal Leadership	-0.319996	0.203549	-1.572	8355

Table C.20. Interaction of School Enrollment and Principal Leadership – Reading—Continued

Fixed effects	Coefficient	SE	t-ratio	df
Enrollment - Small	-1.065799*	0.528489	-2.017	8355
Enrollment - Large	-0.690208	0.456868	-1.511	8355
Enrollment Small * Principal Leadership	-0.597313	0.652168	-0.916	8355
Enrollment Large * Principal Leadership	-0.589354	0.445131	-1.324	8355

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.21. Interaction of School Enrollment and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.937723***	1.481485	22.233	8355
School Climate	-0.266910	0.651132	-0.410	8355
Enrollment - Small	0.928352	2.732842	0.340	8355
Enrollment - Large	-0.923836	2.245259	-0.411	8355
Time (Slope)	35.802489***	0.926140	38.658	694
School Climate	-0.198964	0.418033	-0.476	8355
Enrollment - Small	-1.045375*	0.529450	-1.974	8355
Enrollment - Large	-0.667977	0.461110	-1.449	8355
Enrollment Small * School Climate	0.054122	1.138105	0.048	8355

Table C.21. Interaction of School Enrollment and School Climate – Reading —Continued

Fixed effects	Coefficient	SE	t-ratio	df
Enrollment Large * School Climate	0.388905	0.921057	0.422	8355

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.22. Interaction of School Enrollment and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.057291***	1.136054	21.176	8241
Teacher Collaboration	-0.248607	0.271914	-0.914	8241
Enrollment - Small	2.394502**	0.839038	2.854	8241
Enrollment - Large	1.186013	0.869546	1.364	8241
Time (Slope)	28.112552***	0.733287	38.338	694
Teacher Collaboration	0.890711***	0.184889	4.818	8241
Enrollment - Small	-0.978615*	0.436269	-2.243	8241
Enrollment - Large	-0.550274	0.356686	-1.543	8241
Enrollment Small * Teacher Collaboration	-0.817026	0.467578	-1.747	8241
Enrollment Large * Teacher Collaboration	-0.389089	0.438237	-0.888	8241

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.23. Interaction of School Enrollment and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.147704***	1.136983	21.238	8241
Principal Leadership	0.184162	0.249269	0.739	8241
Enrollment - Small	0.043007	1.172294	0.037	8241
Enrollment - Large	0.982378	1.304985	0.753	8241
Time (Slope)	28.151068***	0.732939	38.408	694
Principal Leadership	-0.064642	0.159513	-0.405	8241
Enrollment - Small	-1.050137*	0.431576	-2.433	8241
Enrollment - Large	-0.556777	0.357269	-1.558	8241
Enrollment Small * Principal Leadership	0.307847	0.353750	0.870	8241
Enrollment Large * Principal Leadership	-0.163454	0.370243	-0.441	8241

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table C.24. Interaction of School Enrollment and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.153788***	1.137628	21.232	8241
School Climate	0.268191	0.594536	0.451	8241
Enrollment - Small	1.197182	1.861943	0.643	8241
Enrollment - Large	-0.740501	1.812972	-0.408	8241
Time (Slope)	28.151712***	0.733494	38.380	694
School Climate	-0.588725	0.357155	-1.648	8241
Enrollment - Small	-1.050321*	0.434060	-2.420	8241
Enrollment - Large	-0.545804	0.358227	-1.524	8241
Enrollment Small * School Climate	-0.079368	0.782599	-0.101	8241
Enrollment Large * School Climate	0.517124	0.751374	0.688	8241

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table C.25. Interaction of School Minority Enrollment and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.973508***	1.479894	22.281	8355
Teacher Collaboration	-0.273263	0.627857	-0.435	8355
Minority Enrollment - Low	-0.147793	1.237587	-0.119	8355
Minority Enrollment - High	-1.059860	1.563578	-0.678	8355
Time (Slope)	35.787463***	0.925246	38.679	694
Teacher Collaboration	0.983926***	0.247329	3.978	8355
Minority Enrollment - Low	-1.490261***	0.444518	-3.353	8355
Minority Enrollment - High	1.462025**	0.474807	3.079	8355
Minority Enrollment Low * Teacher Collaboration	-0.175921	0.644657	-0.273	8355
Minority Enrollment High * Teacher Collaboration	-0.294220	0.802141	-0.367	8355

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table C.26. Interaction of School Minority Enrollment and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.924952***	1.479665	22.252	8355
Principal Leadership	0.750809	0.458453	1.638	8355
Minority Enrollment - Low	0.389169	1.744530	0.223	8355
Minority Enrollment - High	-1.959662	2.130021	-0.920	8355
Time (Slope)	35.799756***	0.925073	38.699	694
Principal Leadership	-0.316361	0.204783	-1.545	8355
Minority Enrollment - Low	-1.510621***	0.439229	-3.439	8355
Minority Enrollment - High	1.448163**	0.477148	3.035	8355
Minority Enrollment Low * Principal Leadership	-0.253527	0.512548	-0.495	8355
Minority Enrollment High * Principal Leadership	0.121489	0.600924	0.202	8355

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table C.27. Interaction of School Minority Enrollment and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.944312***	1.478928	22.276	8355
School Climate	0.097595	1.008027	0.097	8355
Minority Enrollment - Low	0.221889	2.578330	0.086	8355
Minority Enrollment - High	-0.249369	2.885405	-0.086	8355
Time (Slope)	35.795970***	0.923447	38.763	694
School Climate	-0.193891	0.422654	-0.459	8355
Minority Enrollment - Low	-1.506675***	0.439556	-3.428	8355
Minority Enrollment - High	1.435283**	0.478212	3.001	8355
Minority Enrollment Low * School Climate	-0.288684	1.059163	-0.273	8355
Minority Enrollment High * School Climate	-0.576872	1.190030	-0.485	8355

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.28. Interaction of School Minority Enrollment and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.193149***	1.139944	21.223	8241
Teacher Collaboration	-0.321122	0.415923	-0.772	8241
Minority Enrollment - Low	1.378688	0.847247	1.627	8241
Minority Enrollment - High	-0.445795	0.870983	-0.512	8241
Time (Slope)	28.134865***	0.733138	38.376	694
Teacher Collaboration	0.901809***	0.185115	4.872	8241
Minority Enrollment - Low	-1.714521***	0.345032	-4.969	8241
Minority Enrollment - High	1.006661**	0.397364	2.533	8241
Minority Enrollment Low * Teacher Collaboration	-0.126060	0.437898	-0.288	8241
Minority Enrollment High * Teacher Collaboration	-0.397063	0.472381	-0.841	8241

Note. *** $p \leq .001$; ** $p \leq .01$, * $p \leq .05$

Table C.29. Interaction of School Minority Enrollment and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.146715***	1.134332	21.287	8241
Principal Leadership	0.318780	0.334416	0.953	8241
Minority Enrollment - Low	1.761915	1.211810	1.454	8241
Minority Enrollment - High	-1.120395	1.329617	-0.843	8241
Time (Slope)	28.147733***	0.732662	38.418	694
Principal Leadership	-0.080651	0.160566	-0.502	8241
Minority Enrollment - Low	-1.728517***	0.342361	-5.049	8241
Minority Enrollment - High	0.986509**	0.393661	2.506	8241
Minority Enrollment Low * Principal Leadership	-0.180763	0.353306	-0.512	8241
Minority Enrollment High * Principal Leadership	-0.003981	0.397090	-0.010	8241

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.30. Interaction of School Minority Enrollment and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.187090***	1.135942	21.293	8241
School Climate	0.088161	0.795697	0.111	8241
Minority Enrollment - Low	0.666117	1.974848	0.337	8241
Minority Enrollment - High	-2.715650	1.958387	-1.387	8241
Time (Slope)	28.138411***	0.732985	38.389	694
School Climate	-0.582475	0.352301	-1.653	8241
Minority Enrollment - Low	-1.723012***	0.342508	-5.031	8241
Minority Enrollment - High	1.004054**	0.393655	2.551	8241
Minority Enrollment Low * School Climate	0.208786	0.816058	0.256	8241
Minority Enrollment High * School Climate	0.681846	0.831079	0.820	8241

Note. *** $p \le .001$; ** $p \le .01$, * $p \le .05$

Table C.31. Interaction of School FRPL and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.888243***	1.484080	22.161	8356
Teacher Collaboration	-0.574731	0.460223	-1.249	8356
FRPL	-0.016553	0.016140	-1.026	8356
Time (Slope)	35.814296***	0.926874	38.640	694
Teacher Collaboration	0.980917***	0.244679	4.009	8356
FRPL	-0.042957***	0.008190	-5.245	8356
FRPL * Teacher Collaboration	0.004127	0.008300	0.497	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.32. Interaction of School FRPL and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.965598***	1.480659	22.264	8356
Principal Leadership	0.272055	0.382050	0.712	8356
FRPL	-0.036797	0.022707	-1.620	8356
Time (Slope)	35.787744***	0.924880	38.694	694
Principal Leadership	-0.301289	0.201455	-1.496	8356
FRPL	-0.042397***	0.008175	-5.186	8356
FRPL * Principal Leadership	0.008338	0.006292	1.325	8356

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.33. Interaction of School FRPL and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.891633***	1.480847	22.211	8356
School Climate	0.407970	0.813795	0.501	8356
FRPL	0.024623	0.031175	0.790	8356
Time (Slope)	35.828148***	0.924817	38.741	694
School Climate	-0.189055	0.418145	-0.452	8356
FRPL	-0.043467***	0.008243	-5.273	8356
FRPL * School Climate	-0.014175	0.012445	-1.139	8356

Table C.34. Interaction of School FRPL and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.230516***	1.141781	21.222	8242
Teacher Collaboration	-0.305499	0.338832	-0.902	8242
FRPL	0.000349	0.011668	0.030	8242
Time (Slope)	28.125663***	0.734168	38.310	694
Teacher Collaboration	0.897984***	0.184180	4.876	8242
FRPL	-0.024895***	0.006954	-3.580	8242
FRPL * Teacher Collaboration	-0.003959	0.005793	-0.683	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.35. Interaction of School FRPL and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.173389***	1.135364	21.291	8242
Principal Leadership	0.344101	0.296554	1.160	8242
FRPL	0.003511	0.016443	0.214	8242
Time (Slope)	28.142374***	0.732424	38.424	694
Principal Leadership	-0.075509	0.160083	-0.472	8242
FRPL	-0.025162***	0.006934	-3.629	8242
FRPL * Principal Leadership	-0.003113	0.004654	-0.669	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.36. Interaction of School FRPL and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.116667***	1.140222	21.151	8242
School Climate	0.835362	0.671960	1.243	8242
FRPL	0.018480	0.020972	0.881	8242
Time (Slope)	28.171541***	0.734202	38.370	694
School Climate	-0.585312	0.352031	-1.663	8242
FRPL	-0.025458***	0.006945	-3.666	8242
FRPL * School Climate	-0.010692	0.008653	-1.236	8242

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.37. Interaction of School Type and Teacher Collaboration – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.975653***	1.478469	22.304	8357
Teacher Collaboration	-0.391730	0.328399	-1.193	8357
School Type - Private	-1.441126	1.024019	-1.407	22157
Time (Slope)	35.788442***	0.924507	38.711	694
Teacher Collaboration	0.974606***	0.244611	3.984	8357
School Type - Private	-1.448072	1.793685	-0.807	694
School Type – Private * Teacher Collaboration	-2.332943**#	0.736674	-3.167	22157

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

Table C.38. Interaction of School Type and Principal Leadership – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.955674***	1.478734	22.286	8357
Principal Leadership	0.611629*	0.267831	2.284	8357
School Type - Private	-1.161015	1.902858	-0.610	22157
Time (Slope)	35.793691***	0.924254	38.727	694
Principal Leadership	-0.300469	0.202242	-1.486	8357
School Type - Private	-1.375282	1.885652	-0.729	694
School Type – Private * Principal Leadership	0.463904	4.005321	0.116	22157

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.39. Interaction of School Type and School Climate – Reading

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	32.975143***	1.478911	22.297	8357
School Climate	-0.147178	0.561772	-0.262	8357
School Type - Private	-1.283114	1.545381	-0.830	22157
Time (Slope)	35.799956***	0.923742	38.755	694
School Climate	-0.198334	0.418697	-0.474	8357
School Type - Private	-1.201756	1.602040	-0.750	694
School Type – Private * School Climate	-7.900808	4.997288	-1.581	22157

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.40. Interaction of School Type and Teacher Collaboration – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.177845***	1.135759	21.288	8243
Teacher Collaboration	-0.442813	0.243596	-1.818	8243
School Type - Private	-2.156723	2.023358	-1.066	22127
Time (Slope)	28.140861***	0.732392	38.423	694
Teacher Collaboration	0.893591***	0.184583	4.841	8243
School Type - Private	-2.325381	2.548377	-0.912	694
School Type – Private * Teacher Collaboration	-1.201647	1.293416	-0.929	22127

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05

Table C.41. Interaction of School Type and Principal Leadership – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.159712***	1.135947	21.268	8243
Principal Leadership	0.214143	0.213923	1.001	8243
School Type - Private	-1.812037	2.592923	-0.699	22127
Time (Slope)	28.149027***	0.732387	38.435	694
Principal Leadership	-0.072633	0.160076	-0.454	8243
School Type - Private	-2.393754	2.480859	-0.965	694
School Type – Private * Principal Leadership	-1.934921**#	0.609134	-3.177	22127

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

Table C.42. Interaction of School Type and School Climate – Mathematics

Fixed effects	Coefficient	SE	t-ratio	df
Intercept	24.185168***	1.136108	21.288	8243
School Climate	0.396277	0.487126	0.814	8243
School Type - Private	-2.090281	2.277552	-0.918	22127
Time (Slope)	28.151954***	0.732059	38.456	694
School Climate	-8.691035***#	2.480101	-3.504	22127
School Type - Private	-2.142885	2.217287	-0.966	694
School Type – Private * School Climate	-0.583143	0.351831	-1.657	8243

Note. *** p ≤ .001; ** p ≤ .01, * p ≤ .05
The p-values above marked with a "#" should regarded as a rough approximation.

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