ABSTRACT

Title of Dissertation:	MEASURING THE LIMITS: WHEN DOES LONGITUDINAL TEACHER ATTRITION BECOME PROBLEMATIC?
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Researchers have long examined the magnitude and causes of teacher turnover, emphasizing its variability across settings, and observed potential effects on schools and students (Gershenson et al., 2018; Goldhaber & Theobald, 2021; Holme et al., 2017; Ingersoll, 2001). While teacher attrition is often framed as excessively high and problematic (Dias-Lacy & Guirguis, 2017; Neason, 2014; Seidel, 2014) and past scholars have documented harm to students based on exposure to attrition (Henry & Redding, 2020; Ronfeldt et al., 2013), attrition is not fully avoidable. As scholars have begun to attend to the longitudinal nature of attrition within schools including episodic (temporary high attrition), chronic (sustained high attrition across multiple years), and cumulative attrition (accumulation of loss over time), it is often assumed that elevated patterns over the long term will necessarily be even more harmful to students. Yet, existing research offers little insight into when turnover shifts from typical and manageable to atypical and harmful. This study builds on the existing literature (Holmes et al., 2019) by conducting descriptive and inferential analyses to identify policy-relevant measures for episodic, chronic, and cumulative attrition.

Using 12 years of statewide data from Maryland public schools, this dissertation confirms that schools experience a wide range of attrition patterns over time, with the average school

experiencing a 1-year episodic attrition rate of 14.5%, a chronic 3-year average attrition rate of just under 15%, and a cumulative 3-year attrition rate of 37%. While some schools do experience 1-year attrition rates above 60% and 3-year average attrition rates above 50%, these schools represent outliers, and only a small subset of schools lose more than 30% repeatedly.

Further, while chronic and cumulative attrition have been theorized as distinct (Holme et al., 2017), this study demonstrates that schools with above-average rates of 3- to 5-year average attrition also tend to be schools experiencing above-average rates of 3- to 5-year cumulative attrition. This finding suggests these patterns reinforce each other rather than occur independently and challenges the utility of analyzing them separately for policy and practice.

Moreover, nonlinear regression analyses reveal minimal association between 1- to 3-year average attrition and student achievement when attrition is below 30%, but there are significant declines in ELA and math performance when rates exceed 30%. Thus, while high chronic attrition rates (3-year average attrition rates) are highly uncommon, they are associated with severe consequences for students and may be driving the effects previously observed in past studies using linear models robust. These patterns are robust to alternative model specifications, including differing functional forms and the inclusion of school year fixed effects.

This study refined the measurement of chronic attrition and supports the use of nonlinear models to examine their effects. It also offers key policy insights by highlighting both the potential severity and relative rarity of the most harmful attrition environments as findings support shifting policy focus from generalized turnover concerns to monitoring persistent, high-level attrition driven by deeper organizational challenges.

MEASURING THE LIMITS: WHEN DOES LONGITUDINAL TEACHER ATTRITION BECOME PROBLEMATIC?

By

Erin Janulis

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Doctor of Philosophy
2025

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Dedication

For Betty, who helped me believe this is where I belong.

Acknowledgements

This research was supported by the Maryland Longitudinal Data System (MLDS) Center. I am grateful for the assistance provided by the MLDS Center. All opinions are the author's and do not represent the opinion of the MLDS Center or its partner agencies.

This has been a long road. Along the way, I experienced the loss of my first advisor and mentor, Dr. Betty Malen, a global pandemic, and the incomparable joys and challenges that come with raising two young children. I would not have reached this moment without the support of the amazing community of faculty, fellow students, friends, and family who have supported me along this journey.

To my committee—Dr. David Blazar, Dr. Segun Eubanks, Dr. Jing Liu, Dr. Campbell Scribner, and Dr. Laura Stapleton—thank you for sharpening my thinking, challenging my methods, and pushing my work in meaningful and rigorous directions. A special thanks to Dr. Blazar for your steady guidance and calming presence throughout.

I'm also grateful to other current and former UMD faculty who shaped my development as a scholar. Drs. Robert Croninger, Claudia Galindo, Ethan Hutt, and Jennifer King Rice thank you all for your early mentorship and for helping me build a strong foundation. I am especially thankful for the guidance of Dr. Betty Malen, whose insistence on clarity and conviction continues to shape my writing and thinking, and without whose early encouragement, I may never have had the confidence to pursue this path.

To Drs. Casey Archer, Alisha Butler, Pamela Callahan, Bradley Quarles, Kristin Sinclair, thank you for being my community and my accountability team. You've helped sharpen my thinking and sustain my motivation. I know this work is better because of our conversations and your friendship. Thanks also to countless other colleagues at the University of Maryland, the

Office of the State Superintendent, and WestEd who have offered encouragement and shared wisdom over the years.

Finally, to my husband, Michael, and our two children, Abigail and Evan—thank you for your patience, love, and unwavering support over these ten years. I know I’ve often been distracted, but I hope I’ve also shown you the value of following your passions and dedicating yourself to work that matters.

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Chapter 1: Introduction

Statement of the Problem

Organizational theory suggests that even healthy organizations should expect some amount of turnover. In fact, many scholars suggest that turnover can have numerous benefits for organizations. Employee turnover can infuse organizations with new ideas, and the departure of poor performers can improve firm performance (Dalton & Todor, 1979; Wallace & Gaylor, 2012). This body of theory, however, maintains that at certain points, turnover can also become disruptive to the health of the organization and can decrease performance (Osterman, 1987; Shaw et al., 2005). Taken together, this suggests that employee turnover can have varying effects on an organization depending on the shape, magnitude, and composition of the turnover experience.

Within school systems, specifically, a large body of research across multiple decades has focused on the magnitude, trends, causes, and contributing factors of teacher turnover. This sizable body of literature offers great insight into the settings in which we might expect to experience higher-than-average turnover (Gershenson et al., 2018; Hanushek et al., 2004; Ingersoll, 2001), the range and magnitude of turnover we might expect in differing settings (Feng, 2010; Goldhaber & Theobald, 2021; Papay et al., 2017; Sutcher et al., 2016), and the magnitude of the harm (or benefit) that different forms of annual teacher turnover have on student achievement (Dee & Wyckoff, 2017; Henry & Redding, 2020; Ronfeldt et al., 2013).

Despite theory suggesting that turnover can have complex and varying effects on organizations, the body of literature on schools (with limited exceptions) largely frames the issue of teacher turnover as being high and cause for grave concern. For example, one statistic, often stated as fact without attribution, is that 50% of teachers leave the profession within their first five years (Dias-Lacy & Guirguis, 2017; Neason, 2014; Seidel, 2014). Yet despite this statistic being a high-end estimate of a study conducted two decades ago (Fensterwald, n.d.; Ingersoll, 2003), individuals often cite this statistic as evidence that teacher turnover is consistently and untenably high and that the education sector must more urgently attend to teacher recruitment and retention. However, teachers turnover at rates comparable to other female-dominated, service-focused positions like nursing (Ingersoll, 2001). This type of framing may be intended to motivate action. Still, when the problem is one, like turnover, that can never be fully eliminated, these calls lack practical utility for policymakers and practitioners. After all, despite three decades or more of concerns about the stability of the teacher workforce, student achievement has steadily risen over this period (Peterson, 2022).

Despite a more generalized concern for the teacher workforce, one well-substantiated concern is how historically marginalized students are disproportionately exposed to higher teacher turnover rates. Low-income and Black and Brown children are far more likely to attend schools with high turnover rates compared to White middle-class children (Allensworth et al., 2009; Carver-Thomas & Darling-Hammond, 2017; Hanushek et al., 2004). Given the importance of teachers in driving student achievement (Gershenson, 2016; Gershenson et al., 2018; Hanushek, 2016; Hanushek & Rivkin, 2010) and the likelihood that historically disadvantaged students are more likely to experience teacher turnover, these issues remain worthy of our attention.

Part of the difficulty lies in that, despite the insights gained from this vast body of work, the teacher turnover literature provides little insight into how and when these patterns move from typical and healthy to atypical and harmful, as suggested by organizational theory. The landmark work of Ronfeldt et al. (2013) linking grade-level turnover to reduced student achievement may tell us that a student who attends a school where 100% of the grade-level teachers are new will likely perform less well in math or ELA than if the student attended a school where none of the teachers at their grade level are new, still, it does not offer insight into where turnover rates become particularly concerning. Is it after 25% of the grade level turns over, or perhaps not until 50%? And what about more generalized turnover school wide? Can this, too, impact student outcomes? To what extent?

Furthermore, the terrain becomes even more complex when considering how these patterns unfold within schools or systems over time. Across four major studies that analyze longitudinal measures of attrition, there is a striking lack of consensus on what measures or time frames are worthy of tracking. For example, some studies focus on the relative thresholds of their sample, describing the 10% of schools experiencing the highest rate of turnover over five years (Allensworth et al., 2009), while others focus on 6-year retention rates in the field (Ingersoll, 2003) or 3-year permanent turnover rates in schools (Sorensen & Ladd, 2020). Still, others have suggested a range of metrics that could be used to measure school-level longitudinal attrition patterns (Holme et al., 2017), all of which differ from the measures used in the previously cited work. While each of these choices may be useful based on the goals of their individual studies or the availability of data, the use of differing measures makes it difficult to compare and compile insight across studies. It makes it particularly difficult for policy makers and practitioners to have consistent guidelines to drive decision making.

Purpose of the Study

This dissertation addresses the need for more policy-relevant measures of teacher turnover by using the Maryland Longitudinal Data System (MLDS) statewide longitudinal data to identify consistent annual and longitudinal measures of one form of turnover: attrition. In this dissertation, I built on previous work in organizational theory and teacher turnover and attrition by examining a specific hypothesis that there are a series of inflection points where turnover within schools across years becomes particularly harmful to schools and students. This dissertation aims to explore that hypothesis in a way that provides a data-driven set of measures and benchmarks that researchers and practitioners could use to monitor and prioritize intervention. To do that, I applied a validity argument framework (Kane, 1990, 2006) that allowed me to use data to systematically test the following three assumptions, which, if confirmed, support the central hypothesis.

Assumption 1 (A1): Over time, schools experience different forms of longitudinal attrition.

Assumption 2 (A2): Some degree of teacher attrition is typical within a school.

Assumption 3 (A3): Atypical forms of teacher attrition are disruptive to students, and more disruptive forms of teacher attrition will be associated with more severe negative student outcomes.

In particular, I used this inquiry to refine three particular atypical attrition constructs proposed by Holme et al. (2017):

1. Episodes of instability (a measure of temporary high turnover that returns to stable staffing patterns),
2. Chronic instability (a measure of turnover across multiple years), and
3. Cumulative instability (a measure of the proportion of staff lost over time).

I reframed these as attrition constructs specifically (episodic attrition, chronic attrition, and cumulative attrition) and used the argument validity framework to probe the data to develop data-driven and actionable metrics for each construct.

Study Significance

This dissertation aims to make three key contributions to the field. First, I extend the understanding of the relationship between longitudinal teacher attrition patterns and student outcomes. Second, I establish data-informed measures and thresholds of longitudinal teacher attrition that researchers, policymakers, and practitioners can use. Finally, I demonstrate how an argument-based validity approach can also be used to inform the development of new measures and a mechanism for validating existing ones.

This study contributes to both research and policy by identifying thresholds at which teacher attrition becomes harmful to student outcomes and offering concrete guidance on how schools and districts might monitor and respond to chronic instability. Findings suggest that sustained average attrition rates of 30% or more over three years represent a critical tipping point for student achievement, yet only a small subset of schools—often clustered in larger districts—reach this level of instability. This highlights the need to temper generalized crisis narratives and instead focus policy efforts on schools experiencing persistent, high-level attrition. The strong overlap between differing attrition patterns also suggests that these issues stem from deeper, structural challenges within schools, pointing to the importance of long-term monitoring and targeted interventions, including improvements to working conditions and data systems capable of tracking multi-year trends.

Summary

Chapter 1 has provided this project's motivation and the hypotheses guiding this inquiry. Chapter 2 offers an overview of the theoretical framework, key constructs guiding this inquiry, the assumptions this project tests, and the motivating theoretical and empirical literature that supports these assumptions. Chapter 3 describes the methods and analysis I use to answer these questions. Chapter 4 presents the key findings and implications related to A1 and A2, along with methodological refinements made to the analysis of A3. Chapter 5 presents key findings and implications of A3, and finally, Chapter 6 summarizes this study's contribution to the field, policy implications, and implications for future research.

Chapter 2: Conceptual Framework & Motivating Literature

Theoretical Frames and Key Constructs

This section clarifies several key constructs used in this paper as well as highlights the literature motivating this study. First, I discuss two key theoretical frames that inform how this study conceptualizes the relationship between attrition and student outcomes. The first, organizational theory, is not specific to the field of education, but serves as a foundation to help understand how employees of any organization and their choices in remaining or departing an organization can affect the stability and effectiveness of the organization. The second, Ronfeldt et al.'s (2013) constructs of compositional and disruptive effects of teacher attrition, provides a more specific framing of how teacher departures from schools have consequences for students. These concepts inform the assumptions that guide this study and the analytic approaches used to test those assumptions. Next, I summarize an argument-based approach to validity as proposed by Kane (1990), and propose its utility as a generative approach for establishing policy-relevant benchmarks for newly developed measures. Finally, I apply Kane's approach to the proposed constructs by outlining the key testable inferences that I intend to examine in this study and the past research that motivates the selection of these inferences as key to building the validity argument.

Organizational Theory

Most organizational theorists acknowledge that some turnover is essential to maintaining a healthy environment for any organization (Dalton & Todor, 1979; Staw, 1980). Others also emphasize that too much turnover can have harmful impacts not only on the organization but on the quality of the outputs produced by the organization (An, 2019; Moon, 2017) as well as the individuals within that organization (Castro, 2023; DeMatthews et al., 2022; Ingersoll, 2001).

The impact of turnover depends partly on the particular individuals turning over and their organizational roles. When individuals can be easily substituted, their departure is less likely to cause disruption (Braverman, 1974). In organizations where commitment and cohesion are important, turnover affects the institution more dramatically (Kanter, 1977; Likert, 1967). Furthermore, scholars emphasize that after turnover reaches a high enough threshold that the practice becomes routine, the impacts of turnover on the organization tend to taper off (Meier & Fryar, 2008; Shaw et al., 2005).

One group of scholars applying the organizational theory framework to school settings often describes teachers as important for organizational coherence. Teachers are seen as crucial to schools as organizations due to their role in driving school improvements. Many scholars consider stable teacher populations as a necessary condition for successful school improvement (Bryk et al., 2010; Coleman & Hoffer, 1987; Goodland, 1984; Grant, 1988). Organizational progress and improvement planning are hindered when resources must be reallocated to catch up with new staff and build buy-in from new staff year after year. Given the importance of teacher buy-in to successful reform implementation (Grant, 1988; Lipsky, 1980; Reyes, 1990), as well as the professional expertise of these individuals (Bryk et al., 2010), having to revisit key stages and reassess building capacity puts schools at a disadvantage for long-term success.

Furthermore, scholars identify several crucial functions that teachers hold in schools that benefit the organization. The importance of these functions suggests that excessive attrition can undermine these dynamics. Coleman and Hoffer (1987) argued that high school students benefit from tight-knit intergenerational functional communities (an intergenerational group sharing the same social structures and geography). The connectedness of these communities builds social capital (relations between people) as students and teachers develop and maintain relationships throughout multiple years of schooling. This social capital creates human capital (skills and capabilities that make people more productive) as their investment in the relationships between teachers and students ensures students get more out of their time at school in and out of the classroom. Coleman and Hoffer argued that this is impossible without social interactions between a stable set of individuals over time to allow for norms to be created and enforced. For this form of capital to develop, it is necessary for a stable group of people to maintain these social networks and for social capital to accumulate between them.

All of these concerns suggest that the stability of the labor force is important to the organization and schools in particular. These theories also suggest that the absence of that stability could negatively affect the organization. Further, Ingersoll (2001) suggested that this instability, caused by high rates of attrition, could also generate undesirable working conditions, such as additional mentoring responsibilities and redundant trainings. This instability and increased responsibility, Ingersoll argued, can contribute to additional attrition in the future. This reciprocal relationship suggests attrition could be a particularly complex problem to tackle.

Compositional and Disruptive Effects

While organizational theory provides a foundation for the value of employees and teachers to the organization, given that this study focuses on schools specifically, Ronfeldt et al. (2013) provided a more specific explanation for how teacher attrition causes changes in student outcomes. The authors proposed two primary mechanisms for considering teacher attrition's effects: compositional and disruption effects. These authors theorized that teacher turnover can affect students through changes in the composition of teacher quality, which they suggested are compositional effects. This mechanism can produce either positive or negative changes in student outcomes. These results serve as justification for policies that systematically remove the lowest-performing teachers as a mechanism for improving student outcomes (Dee & Wyckoff, 2017; Hanushek, 2009). Conversely, if departing teachers are of higher quality than those who fill their positions, then the expectation would be that this change would negatively affect student outcomes. However, if departing teachers are of lesser quality than those who fill their positions, the opposite will be true. Ronfeldt et al. found that, on average, 100% attrition of grade-level teachers reduces student achievement by 0.086 (0.011) standard deviations in math and 0.049 (0.01) standard deviations in ELA compared to grade levels that experienced zero turnover. After controlling for indicators of teacher quality (teacher experience or value-added estimates), the impacts decrease from –0.059 (0.011) to –0.040 (0.012) in math and from –0.031 (0.01) to –0.027 (0.012) in ELA. This decrease shows that those compositional effects drive a portion of the total effect. Likewise, the fact that these estimates, although reduced, still remain significant, suggests that other effects are at play.

To speak to this other factor, Ronfeldt et al. proposed disruptive effects*,* which describe the impact that departure has on the school community or subgroups within the school and the potential impact that departure has on the quality of those left behind. The idea is that, aside from any change in quality, the disruption caused by those in and around the classrooms directly affected by turnover can have some effect on other teachers and students. For example, while a stronger teacher may replace a poor-performing teacher, the impact of providing mentoring and training to the new teacher may adversely affect the teachers around them as their time and effort become split between supporting their students and supporting their new colleagues. The authors go on to suggest that this split focus affects their ability to provide high-quality instruction. Conversely, turnover theory (a subset of organizational theory) suggests that some disruption is healthy for an institution and that the infusion of new ideas and the departure of poor performers is part of building a healthy workplace (An, 2019; Dalton & Todor, 1979; Wallace & Gaylor, 2012). This suggests that similar to compositional effects, the disruption could produce positive effects if the new staff required less support or if the new staff introduced new, more effective practices to their colleagues. Still, it would be likely that at a certain intensity, the disruption would ultimately become harmful to the school. At the grade level, Ronfeldt et al. found that even students in classrooms whose teachers had remained in the same grade and school from the previous year perform significantly worse when turnover is greater (–0.054 in math and –0.035 in ELA). Suggesting even those students who do not have direct exposure to teachers new to their building or role experience the effects of this instability within the grade-level teaching staff.

Moreover, when schools and students experience disruptive and compositional effects concurrently, the significant disruptive impact of staffing changes could counteract any positive compositional changes. Past research documented how schools experiencing multiple years of high turnover cause disruptions to teachers when returning teachers are expected to acclimate new teachers to the school culture and environment (Guin, 2004). Teachers also reported receiving duplicative professional development to catch new teachers up to existing initiatives, which limits the growth of existing teachers. With all of these pressures placed on existing teachers, it seems likely that at some point, this school-wide disruption could become significant enough to offset compositional benefits, particularly without a specific policy lever or incentive to ensure departing teachers were significantly less skilled compared to incoming teachers (Dee & Wyckoff, 2017). The more teachers leave, the more likely that remaining teachers (and their students) are impacted by the disruptions. Furthermore, while many scholars have leveraged variation or content area attrition variation to estimate effects on student achievement, past research has not examined the relationship between school-wide instability on student outcomes. What remains unclear in the existing literature is at what point this shift happens—in particular, at what rate of turnover, over how many years, and at what magnitude of associated student harms.

While Ronfeldt et al.'s (2013) study sought in part to disentangle disruptive versus compositional effects, this work does not seek to investigate these constructs separately. Instead, this study builds on this prior work in two ways. First, I extend the idea that not all teacher attrition is necessarily harmful and suggest thresholds for separating typical healthy attrition and atypical and unhealthy attrition. Additionally, while Ronfeldt et al. focused on attrition and turnover at the grade level in a single year, I examine two additional dimensions of harmful attrition: the impact of instability at the school level and how that pattern of instability is associated with differing student outcomes.

This work specifically responds to calls from other scholars (Holme et al., 2017; Sorensen & Ladd, 2020) to understand how these proposed patterns develop within schools over time. To pursue this goal, I focus on three constructs proposed by others (Holme et al., 2017) as possible distinct longitudinal attrition patterns: episodic, chronic, and cumulative. These constructs serve as tools to describe patterns of attrition over multiple years. Thus, even if a school experiences the same turnover rate in a given year, the pattern of those rates over time may be associated with differing levels of disruption once the pattern is established.

Examples help illustrate the conceptual differences between these three key attrition types. The thresholds described in these scenarios are set arbitrarily to illustrate the conceptual distinctions between attrition constructs, and this dissertation identifies data-driven thresholds. For this exercise, assume that 25% is a high attrition rate (this study probes for more authoritative benchmarks) and consider three hypothetical schools. School A experiences 10% teacher turnover in Year 1, 25% in Year 2, and 10% in Year 3; this situation describes a school experiencing episodic attrition in that the school experienced one year with higher rates of attrition with relatively lower attrition rates in the year before and after the episode. School B experiences 25% teacher attrition in Years 1 through 3, with turnover concentrated mainly within the same positions (i.e., the fourth grade special education position is vacated three years in a row, or the eighth grade math team turns over repeatedly); this situation could describe a school experiencing chronic attrition. School C experiences 25% teacher turnover across Years 1 through 3 but across different positions within the school, such that by Year 3, only 25% of the original teachers remain (with 75% of teachers from Year 1 having departed); this situation describes a school experiencing chronic and cumulative attrition because this school is experiencing both a high rate of loss year over year and a high accumulate loss over three years. Conversely, School D could experience 15% teacher attrition in Year 1, a different 20% of teachers depart in Year 2, and another different 15% of teachers depart in Year 3. In this case, the 3-year average attrition rate of 16.6% would not constitute chronic attrition, but given the compositional change, the 50% loss over three years could be considered cumulative attrition.

Across all three scenarios, the school experiences at most 25% teacher attrition in a single year. Yet, one might imagine that each scenario represents quite distinct levels of instability in the school environment. While School A's instability could be harmful to a school environment and cause major compositional shifts, attrition occurring in a single year might produce less change than the instability seen in School B or School C, where it occurs repeatedly over multiple years. Additionally, while a high teacher attrition in School B would create a largely unstable environment, a school losing such a high percentage of staff over time, as in School C, would be even more unstable, as it would inhibit the transfer of institutional knowledge between teachers to keep instructional improvement moving forward. Similarly, even without the high average yearly losses observed in School C, School D could also produce a large amount of instability, given the accumulated loss of 50% of its teaching staff in this short period of time. If these assumptions hold and cumulative attrition produces greater instability than chronic attrition, which, in turn, produces greater instability than episodic attrition, one will also expect that the greater the level of instability that occurs, the greater the negative effects the students would experience.

Despite the fact these three scenarios seem to represent very different teacher staffing patterns as proposed by Holme et al. (2019), the existing literature does not provide clear guidance on defining them concretely, with regard to several dimensions: levels of attrition that shift from typical to atypical, number of years to assess chronic attrition, and percent of staff cumulatively over time. For example, while my example compared schools across three years, that decision was a somewhat arbitrary one. But how many years should we be concerned about? Do patterns shift after two years of high attrition, or maybe three or four? What constitutes high? In my examples, I suggested perhaps 25%, but perhaps harmful instability occurs at 10% or 35%. This dynamic is understudied in the existing literature. Thus, one major goal of this study is to not only consider particular inflection points and benchmarks for each of these constructs but also to compare the magnitude of the associated student outcomes across each attrition pattern to determine at what point each construct is associated with differing outcomes after exposure for a single year and constitutes a unique phenomenon. Furthermore, as highlighted in the discussion of School C, it is possible and likely that there is a significant overlap between these constructs. Just because I might imagine that a school could experience each of these patterns does not mean that, in practice, this occurs. Consequently, this study also probes the extent to which these phenomena are truly distinct in the real world.

Argument-Based Validity

This dissertation employs an argument-based validity approach to establish benchmarks for school-level attrition, aiming to create data-informed measures that capture annual and longitudinal patterns of teacher turnover. This approach is widely adopted in educational research to validate constructs like teacher quality, but here, it is repurposed to develop and refine the constructs of episodic, chronic, and cumulative attrition (Holme et al., 2017). In most inquiries that use an argument-based validity approach, the measure is already established, and this approach is used to validate the appropriateness of that measure. For example, teacher observation tools in use in a specific state may have already established scoring, weighting, and cut scores for the tool. In the case of the constructs I examine, other scholars (Holmes et al., 2019) have proposed these constructs. However, there is no consensus on (a) how to measure the construct precisely or (b) how to interpret the construct. Thus, in this case, I use the standard approach and steps to develop a refined measure of each construct based on a desired interpretation rather than assess the alignment between an existing measure and its proposed interpretation.

Rather than merely assessing the validity of an existing measure, this framework allows for a systematic examination of how best to operationalize these constructs. Through this process, assumptions are interrogated, and the resulting measures are justified based on both theoretical soundness and practical utility. The argument-based validity approach thus ensures that each metric is explicit in what it represents and can be defended with logical connections between assumptions, evidence, and implications, making it especially well-suited for defining complex phenomena like longitudinal attrition.

According to Hughes (2018), questions of validity center on whether the measure captures what it purports to measure and whether it serves its intended purpose in decision-making contexts. This distinction emphasizes a balance between accuracy—reflecting true values—and appropriateness—the measure's utility for real-world application. In this study, appropriateness is prioritized over accuracy because the goal is to create metrics that are practical and meaningful for policymakers. Thus, even though an extremely accurate metric could be developed, a more complex measure that does not align with practical needs would have limited policy utility. Since attrition metrics are relatively straightforward to define, the inquiry emphasizes developing measures that are both interpretable and actionable for monitoring significant attrition patterns.

The validity framework developed by Kane (1990) building off of the work of Cronbach (1988) and Toulmin (2003) underpin this approach, involving three key steps: (1) clearly stating the interpretive argument and embedded assumptions, (2) assembling relevant evidence, and (3) evaluating the assumptions until all inferences within the interpretive argument are plausible. The interpretive argument in this context is constructed to ensure that each metric conveys specific attrition patterns with clear implications for policy and intervention. Meanwhile, the validity argument presents data supporting the interpretive assumptions, including content, construct, and predictive validity. Both arguments are essential; without a defined interpretive argument, the validity argument lacks structure, while without evidence to support it, the interpretive argument is ungrounded. This structure draws on the Toulmin model of argumentation, where evidence and justification are central to the strength of a claim. In this section of the dissertation, I describe the interpretative argument and embedded assumptions, based on theory and prior research.

Typically, the argument-based approach validates existing measures, but in this case, the measures for episodic, chronic, and cumulative attrition are not yet established. As such, the interpretive argument is built from theoretical literature on teacher staffing patterns and their effects on organizational outcomes, specifically student achievement. By comparing and refining thresholds for each construct, this process adopts the standard approach to guide the development of new metrics that meet specific policy needs rather than testing an established measure. In the chapters that follow, the dissertation outlines the interpretive arguments and their embedded assumptions, details the analyses used to test these assumptions, and provides benchmarks that are both theoretically sound and practically relevant for policymakers.

The Interpretive Argument and Assumptions. Policymakers care about teacher attrition for several reasons. Most prominently, teacher attrition harms student academic achievement (Ronfeldt et al., 2013). Additionally, attrition is costly to schools and can harm other improvement efforts, as stability in teaching staff is a necessary condition for successful school reform (Bryk et al., 2010; Guin, 2004).

However, all schools necessarily experience some level of attrition. Teachers retire, move, or choose to pursue other roles, and despite the costs described above, it is not reasonable to assume that schools reduce their attrition entirely. Thus, the interpretive argument guiding this study is that schools experience different forms of attrition and that each distinct form produces varying levels of instability in schools and consequences for students. Following prior literature (Holme et al., 2017), I begin with three major attrition types: episodic, chronic, and cumulative.

Each of these measures is intended to reflect an inherent level of instability, with each form producing more instability than the previous form. I posit that each form of attrition is defined in such a way that the harmful student outcomes associated with it are substantially more severe compared to those associated with disruptive forms of attrition. This argument is a predictive one in that the argument focuses on the extent to which these measures can predict student outcomes; however, rather than being tied to a single outcome, the proposed interpretive argument is that the measures represent the point at which the phenomenon produces multiple harmful student outcomes. I propose that the benchmarks for all three attrition constructs in this investigation signal when a teacher attrition pattern is associated with more harmful student outcomes on ELA state achievement tests and math state achievement tests after exposure to the pattern for one year.

In this case, my analytical argument is supported by three underlying assumptions. Each assumption is then aligned with a set of analytic tests to form the validity argument that is designed to establish relevant benchmarks for each of these measures. Below, I outline the relevant assumptions this project examines and outline a type of evidence used to support each assumption. Each assumption builds upon an argument established through testing of the previous assumption. Thus, while the final assumption is most closely aligned with the initial interpretive argument—regarding the relationship between different forms of longitudinal school-level attrition and student outcomes—confirmation of the final assumptions is not possible without evidence examined under previous assumptions regarding the (a)typicality of attrition and the extent to which different forms of attrition, as proposed in the literature, are distinguishable empirically. Further, details regarding the specific tests and analysis considerations that will form the validity argument are outlined in greater detail in Chapter 3.

A1: Some Degree of Teacher Attrition is Typical within a School. Turnover is an inevitable aspect of any profession. Employees retire, transition to new roles, or leave the workforce for various reasons. While some level of turnover is typical, what constitutes "typical" turnover can differ slightly based on field, context, and geography. For example, past research suggests that teacher attrition in the United States may be high compared to other developed countries (Sutcher et al., 2016). Sutcher et al. calculated U.S. teacher attrition rates to be 7.7% in 2013; comparatively, in Finland, Singapore, and Ontario, Canada, the yearly average attrition is 3–4%. Furthermore, natural end-of-career retirements do not drive these patterns. Much of this attrition in the United States is driven by dissatisfaction with workplace conditions rather than natural end-of-career retirements, with an equal number of teachers leaving for this reason as those who retire (Ingersoll, 2004; Sutcher et al., 2016).

However, these comparisons may not fully capture the unique political, economic, and cultural dynamics of the U.S. educational system. Scholars have argued that while U.S. teachers may leave their roles at higher rates than educators in other countries, their attrition rates align more closely with those of other U.S. service-oriented professions, such as nursing (Henke et al., 2001; Ingersoll, 2001). These complexities underscore the challenge of using a single point of comparison of a single measure to define "typical" turnover within the U.S. teacher workforce.

Adding to this challenge is the significant variation in teacher attrition rates across different schools, districts, and regions. Barnes et al. (2007) documented a 12-percentage-point difference between two large urban districts and a 27-percentage-point difference between two small rural districts. Within urban districts, Papay et al. (2017) observed 1-year attrition rates for novice teachers ranging from as high as 54% in one district to a low of 22% in another. These disparities suggest that turnover patterns are not uniform, and what is typical for one context may be atypical for others. For example, research consistently finds higher turnover rates in schools serving larger populations of minority and low-income students (Allensworth et al., 2009; Guarino et al., 2011; Hanushek et al., 2004; Ingersoll, 2001; Shen, 1997). Additionally, teachers leave low-performing schools at higher rates, exacerbating educational inequities (Allensworth et al., 2009; Guarino et al., 2011; Hanushek et al., 2004).

Geographical and regional factors further complicate the landscape. Teachers in large urban districts often leave at significantly higher rates than their suburban counterparts (Lankford et al., 2002). Additionally, attrition rates tend to be higher in Southern states (Carver-Thomas & Darling-Hammond, 2017) and in some Western states (Stockard & Lehman, 2004). These trends illustrate how teacher turnover varies systematically by location, school demographics, and other contextual factors.

Given the well-documented variation across school settings, I seek to consider thresholds of typicality in a way that is inclusive of a wide variety of settings, not just what is common for a subset of settings. Thus, we would expect that typical attrition would not only occur at least in a majority of the schools across various settings in the sample over the observable time period but also in schools of each subgroup of schools examined in this study. This is not intended to gloss over the heterogeneity that occurs in different school types; rather, I choose this broader frame in an effort to move beyond thinking about typicality from the perspective of a unitary metric (i.e., at or below the mean or median). Furthermore, I do not seek equal representation of schools from differing settings above and below this threshold; instead, I seek to ensure that the establishment that to be a school experiencing a "typical" amount of attrition that school must also fit some idealized school type. This approach is rooted in the goal of this study to produce policy-relevant metrics that would be useful in a wide range of settings.

A2. Over Time, Schools Experience Different Forms of Longitudinal Attrition. A2 seeks to establish whether three constructs of attrition as proposed by prior literature (episodic attrition, chronic attrition, and cumulative attrition) are empirically separate and distinct. The measurement literature commonly refers to this as discriminant validity. This study takes some liberties in its approach to establishing this form of validity, as the three measures of school-level attrition are expected to be distinct but with some overlap (Engellant et al., 2016; Netemeyer et al., 2003). Despite some expected overlap, this approach tests whether episodic, chronic, and cumulative attrition are distinct phenomena experienced by different schools in different ways at different times.

Recent scholarship has shifted attention from annual attrition rates to longitudinal patterns of attrition in schools (Holme et al., 2017; Sorensen & Ladd, 2020). Holme et al. (2017) argued that monitoring turnover using longitudinal measures may better capture the different types of instability experienced by students and staff. These authors focused on three broad categories of school-level attrition described previously (i.e. episodic, chronic, and cumulative) but with additional gradations. Their proposed constructs aim to capture the cumulative and varied impacts of turnover across multiple years based on its severity and nature. These authors suggested longitudinal instability measures can be measured both in absolute and relative rates over a certain number of years or percentage in a given time period; these measures can help identify schools that perpetually deal with high attrition rates rather than just a snapshot of a single year of turnover.

For example, chronic instability was measured by Holme et al. both in absolute terms and as relative rates over a set time period, identifying schools that persistently face high turnover rather than single-year snapshots. Cumulative instability, on the other hand, measures the proportion of staff lost over time, distinguishing schools that experience widespread staff turnover from those struggling with attrition in a few specific positions or fields. This distinction helps illuminate whether broader organizational impacts or localized disruptions are at play.

Despite the thoughtful discussion of potential approaches in their work, Holme et al. provided multiple constructs, all of which could be measured using either absolute or relative thresholds based on any duration of time or intensity. The end result is a large number of options with limited guidance on the practical distinctiveness of each metric.

Holme et al. (2017) explored the prevalence of schools that experience turnover above 30%. The authors found that while 60% of schools in Texas experienced at least one year of turnover above 30%, only 4.4% experienced chronic turnover (30% of their teachers for seven or more years). Notably, rural schools were most likely to experience this form of churn (10.5%), with urban schools (5.1%) and suburban schools (4.2%) closer to the state average. In contrast, urban, suburban, and rural schools experienced cumulative turnover (rate of loss over time) at strikingly similar rates (on average, schools lost over 70% of their teaching force within eight years). These findings suggest that different attrition metrics manifest differently across common school-level features.

While Holme et al. (2017)'s work serves as a foundational framework for this dissertation, their analysis proposed measures with little explanation or justification for the specificity of each measure and without providing a data-driven argument that these constructs are distinct. This assumption, in particular, seeks to explore the distinctiveness of these constructs. One hundred percent overlap between each phenomenon implies that these may not be distinct phenomena (or at least not distinct in data available to researchers and policymakers to act on in distinct ways), and if they are not distinct phenomena, they should not be investigated as distinct patterns. This study focuses on a subset of these constructs with a more narrow focus on attrition specifically (chronic, cumulative, and episodic attrition); furthermore, it expands on prior work by attending to the question of duration and intensity to narrow the focus of future scholars, policymakers, and practitioners on measurable and distinct patterns of concern.

A3: Atypical Forms of Teacher Attrition are Disruptive to Students, and More Disruptive Forms of Teacher Attrition Will be Associated with More Severe Negative Student Outcomes. Assumption 3 again builds on the argument of typicality and distinctiveness by asserting that each form of attrition can be defined by its differential effects on student outcomes. This portion of the argument introduces a predictive validity lens, hypothesizing that distinct patterns of attrition—characterized by their intensity and duration—produce varying levels of disruption that affect students differently. To test this assumption, this study links longitudinal measures of teacher attrition to student achievement outcomes to assess whether differing attrition patterns result in distinct impacts on student success.

Research consistently shows that one-year teacher attrition rates are linked to lower student achievement. As noted earlier, Ronfeldt et al. (2013) estimated that students who were in a grade level experiencing 100% turnover performed 0.082 to 0.102 standard deviations lower in math and 0.049 to 0.060 lower in ELA on state assessments compared to students in a grade level that experienced no turnover in the previous year. Those negative outcomes were more acute for students in schools serving a higher proportion of low-achieving and Black students—highlighting that disadvantaged students, already more likely to experience teacher turnover, are also more likely to bear the brunt of its harmful effects. Importantly, these effects were not limited to classrooms directly affected by departing teachers but extended to students whose teachers remained, suggesting that attrition disrupts grade-level organizational structures in ways that impact all students. Given that this one-year grade-level disruption has been shown to produce effects, it is also likely that a sustained disruption pattern may be associated with even greater harms to outcomes in achievement and that the disruption may extend beyond the grade level itself.

The timing of teacher attrition further exacerbates its effects. Henry and Redding (2020) found that find that mid-year grade-level turnover produces student achievement dips nearly equivalent to the effect of a student having a teacher in their first year of teaching: –0.069 (0.01) in math and –0.051 (0.01) in ELA for elementary students and –0.106 (0.10) in math and –0.042 (0.012) in ELA for middle school students. Other research by Atteberry et al. (2017) showed that even within-school position changes, such as teachers shifting from one grade to another negatively impact student outcomes. While the negative impact of this form of churn is small in comparison to other forms documented above (approximately –0.010 standard deviations on standardized achievement tests), students are much more likely to encounter a churned teacher than a teacher new to the field.

While much of the existing research focuses on annual cycles of attrition or turnover, less is known about how longer-term instability influences student outcomes. Sorenson and Ladd (2020) suggested that longer-term instability may be linked with more acute effects on student achievement. The authors found that students in grade levels with 100% turnover of ELA and math teachers over three years performed 0.134 standard deviations lower in math and 0.072 standard deviations lower in ELA compared to students in grade levels with zero turnover of ELA and math teachers. These findings establish the importance of examining longitudinal instability to better understand its impact on student achievement but stop short of examining this as a school-level phenomenon.

The current study defines student achievement outcomes as evidence of the broader instability caused by attrition (Balfanz & Byrnes, 2012; Brundage et al., 2017; Henry & Redding, 2020; Ronfeldt et al., 2013) and builds upon the existing research to offer a way to capture the nuanced ways in which attrition patterns evolve over time and document their association with student outcomes. This research aims to address this gap by refining longitudinal attrition measures in terms of duration, intensity, and associated student outcomes.

Summary

This chapter has laid the foundation for understanding the assumptions underlying this study's approach to measuring and analyzing teacher attrition. It emphasized the importance of moving beyond annual turnover rates to examine longitudinal patterns of attrition, focusing on chronic, cumulative, and episodic forms. The analysis highlights that while some level of teacher attrition is inevitable and even typical across schools, atypical and more severe forms of attrition can disrupt schools and negatively affect student outcomes.

This chapter began by outlining the three primary conceptual frames that guide this work before describing how I implement Kane's approach to this study by describing the analytic argument and underlying hypothesis that informs that argument and the existing literature that supports the inclusion of each assumption. Having established the theoretical assumptions, next, I describe the data and methods I use to explore and test these three assumptions.

Chapter 3: Data and Methods

In Chapter 2, I developed assumptions about the nature of multiyear teacher attrition in schools as informed by theory and prior literature on this topic. In this chapter I extend this discussion to describe the methods and data used to test those assumptions. This chapter outlines the data sources used to conduct this inquiry as well as methods employed to probe each of the assumptions. I begin by describing the data sources used and the strengths of using this particular data set for this examination. I then provide greater detail on the specific variables used in the analysis. The final section describes the methods employed to interrogate each assumption and how these analyses will contribute to the validity argument.

Data

Maryland Longitudinal Data System (MLDS)

The Maryland Longitudinal Data System (MLDS) serves as the primary data source for this inquiry. MLDS serves as a central repository for individual-level student and workforce data from all levels of education and the State's workforce, including information on all public schools in the state. For this project I use MLDS variables from the Maryland State Department of Education (MSDE).

In addition to the richness of the data source itself, Maryland offers a robust analytical setting to examine. As teacher attrition patterns have been documented to vary significantly across different settings and contexts (Barnes et al., 2007), it is vital that a study examining attrition constructs is not driven by any one district or organizational unit.

Maryland offers a wide range of school types and district types within a relatively small geographic area, including a large city district and exurban, suburban, small city, and rural areas. This ensures that I can include a wide range of school setting types in this study in a single sample. While most students are located in the six largest districts (Montgomery, Prince George's, Baltimore County, Baltimore City, Anne Arundel County, and Howard County), the state is not dominated by a single large school district (as, for example, New York City in New York State).

In addition to the diversity of school and district types found in Maryland, the racial diversity of the student and teacher populations offers a substantial population of several historically underrepresented individuals (Black and Hispanic students and Black teachers). While the state demographics may be more reflective of regional rather than nationwide averages (NCES), the variation in demographics ensures that the sample population reflects a diverse student and teacher pool. Conducting analyses in a setting that contains heterogeneity of student and teacher demographics ensures that the findings can be generalized to a greater variety of schools and settings. While the state of Maryland may undoubtedly have some differences in demographics or density to the United States, the state still offers a strong stand-in on several indicators.

Most of the data used in this analysis comes from the MSDE contributions to the MLDS. This section of the data system includes data on student demographics, school and course enrollment, standardized test scores, and teacher credentials. The data set also includes teacher and staff demographic, employment, and certification data, as well as data on the grade level served and school type (i.e., traditional, charter, alternative, etc.). Data on K-12 schools goes back to the 2007–2008 school year, although data linking student assessments to teachers is unavailable until the 2012–2013 school year. I used data from 2008–2019 to track teachers' attrition patterns for this project. One of the goals of the initial stages of analyses is to consider what subsets of this data are most useful for considering the research questions for this investigation. To supplement data on school urbanicity, not available in the MLDS, I pull on data from the U.S. Department of Education's Common Core of Data (CCD).

The MLDS requires all researchers to adhere to strict data suppression rules to ensure privacy remains intact. For this reason, all data reported in this analysis will be subject to the following suppression rules:

1. No data will be reported for groups with less than 10.
2. Where totals are provided, secondary suppression may also be used to protect the primary suppressed figures as needed.

Sample

Data for this study comes from the academic years 2008–2009 to 2018–2019, with an analysis of student outcomes from 2012–2013 to 2018–2019. I excluded data from 2019 to 2023 as the COVID-19 pandemic resulted in such a dramatic shift in business as usual and likely had a substantial impact both on teacher staffing patterns (Bill et al., 2022; Carver-Thomas et al., 2021; Pressley, 2021) and student achievement (Hammerstein et al., 2021; Lewis & Kuhfeld, 2021) in ways that cannot be otherwise accounted for in this analysis. In addition to this temporal limit, I established sample exclusion/inclusion rules at the school and student levels. At the school level, I excluded (a) schools with less than ten staff members, because small changes are exaggerated in rate calculations in a school this small; and (b) school-year observations where the school was not present in the data in the previous three academic years so that all schools have the opportunity to measure at least one multiyear attrition rate (to measure a single year of attrition I need two years of data: the observed year and the previous year, and each multiyear attrition rate requires one additional year of data). This removed 1.2% of schools and 0.01% of teachers from the sample.

I also excluded the following student observations: (a) students with no test score data, as these are the primary outcomes investigated in this analysis; (b) students with no prior year test score data as prior year outcomes are a key component to leveraging a school-level VAM as described later in this chapter; and (c) students who were enrolled in the school for less than 50% of the school year, as students with a minimal amount of time spent in the school setting would have had less exposure to the specific phenomena of interest. This removed 7% of student observations. Sample summary statistics for the full school sample are displayed in Appendix A.

As outlined in the Methods section below, I further restricted the sample for some inferential analyses to sixth-grade students in middle schools. Appendix B displays sample summary statistics from the restricted sample.

Variables

This section describes the variables included in this investigation and the reasons for their inclusion. I describe how I calculated annual and multiyear school-level attrition rates. Specific metrics associated with each construct will be developed as part of this project's analysis. Next, I outline both student and school variables, including student population, teacher population, and school features.

Attrition. Attrition is not a pre-existing variable in the MLDS. Since my concern for this measure is attrition from the building rather than attrition from the field, I determine attrition based on the absence of a teacher in a school from one academic year to the next. For example, if Teacher A were observed in School 1 in Year 1, but Teacher A was not present in the data for School 1 in Year 2, that teacher would be considered attritted. A school's attrition rate is the number of teachers observed in School 1 in Year 1 who are also observed in School 1 in Year 2, divided by the total number of teachers observed in School 1 in Year 1. This measure lumps all types of departures together, including teachers who leave for nonteaching positions, positions in other public or private schools, or out-of-state positions. I take this approach as any departure could have disruptive and compositional effects, and this approach is similar to other scholars' approaches (Henry & Redding, 2020; Ronfeldt et al., 2013; Sorensen & Ladd, 2020)[1].

Measuring Attrition. One aim of this work is to propose data-informed, policy-relevant longitudinal metrics to arrive at these concrete metrics. In pursuit of this aim, I examined the extent to which specific attrition measures capture unique constructs proposed in the literature.

I started by capturing turnover at the teacher level, tracking the number of teachers who depart in a given year, and then calculating the annual attrition rate by dividing this number by the total number of teachers employed at the beginning of that year, to generate each school's 1-year attrition rate.

To capture longitudinal measures of attrition, I took two approaches. First, I calculated the average attrition rate across multiple years. I refer to these as 2- to 6-year average attrition rates. I used these measures to interrogate the construct of chronic attrition. While the scholars who proposed the construct of chronic instability dichotomized the variables (Holme et al., 2017), this approach deviates from this practice. It offers two significant advantages for this research inquiry. First, employing average rates allowed me to continuously measure attrition rather than losing information through dichotomization. Strict thresholds create the illusion of a greater distinction between rates on either side of a strict threshold. In practice, however, if I were to set

[1] Focusing only on the departures of teachers from the building overlooks some transitions that occur within buildings into noninstructional roles (instructional coach, administrator, etc.). Researchers have not yet fully examined this in great detail, and thus, including internal transitions out of the classroom may slightly under bias my later analysis, as the departure of these individuals from their roles in classrooms may itself produce some disruption as these positions may need to be filled with new-to-building staff.

a 2-year attrition threshold at 75%, a school with two consecutive years of attrition at 75% would be treated differently compared to a school with one year of attrition at 75% and the next year with only 74% attrition, when the two schools patterns are strikingly similar. Using a running average is just as easy to calculate and track for policymakers and allowed me to retain nuance in metrics for these analyses. Second, using average rates helped to consistently incorporate attrition trends across the differing constructs in my analysis. This is valuable because it allowed for better comparison across measures and their potential impact on various outcomes. By considering attrition as a continuous variable, I gained a deeper understanding of how it evolves over time and as it intensifies.

Second, I calculated the share of all teachers who turn over within a given period. I refer to these as 2- to 6-year attrition rates. I used these measures to explore the construct of cumulative attrition. The resulting 2- to 6-year attrition rate is again a continuous variable that quantifies the overall attrition experienced by the school over the chosen time frame. This continuous measurement allowed for statistical analysis and facilitated the examination of trends and patterns in accumulated departures among teachers in the school. These measures, however, may underestimate the total staffing instability a school experiences as teachers who are hired after Year 1 and depart during the observed period are not captured by these rates.

I conducted a series of descriptive and inferential analyses, described below, which inform the development of more concrete and detailed metrics for each construct as I test each of the assumptions in subsequent stages of this project.

Student Characteristics.

Achievement ELA/Math. Like all other U.S. states, Maryland must test students annually in math and ELA, in grades 3 through 8 (and once in high school, though high school students are not included in this analysis, as described below). These annual test scores are included in the MLDS data at the student level. Over the time frame of this study, Maryland administered three different tests (The Maryland State Assessment (MSA) reading and math was administered between 2003–2014, and PARCC ELA and math was administered between 2014–2018, and the Maryland Comprehensive Assessment Program (MCAP) was administered in 2019, which included PARCC items).

To compare outcomes across multiple years, I standardized the data based on the year and the test administered. Achievement variables were included both as the outcome variable of interest and as control variables in the form of the previous year's achievement scores. These student outcomes are widely used in the existing literature (Henry & Redding, 2020; Ronfeldt et al., 2013; Sorensen & Ladd, 2020). Appendix C highlights the impacts observed in past research.

Attendance. This variable describes the number of days missed during the school year. Prior year attendance was included as a control variable as an additional variable to capture past student performance. Additionally, previous studies have linked attendance to student achievement (Gottfried, 2010).

The next five variables serve as control variables in inferential models for student background features that may be related to student academic outcomes and teacher attrition (Noguera & Wing, 2008; Peterson, 2022).

EL Status. This variable was dichotomous, with 1 representing students receiving English learner services and 0 for all other students.

FARMs Status. This variable was dichotomous, with 1 representing students who received free or reduced-price meals and 0 for all other students.

Gender. This variable was dichotomous, with 1 representing males and 0 for females.

Race/Ethnicity. The MLDS includes the following racial categories: American Indian/Alaskan Native, Asian, Black/African American, Native Hawaiian or Other Pacific Islander, and the following additional ethnicity categories: Hispanic-Latino. The MLDS racial and ethnic-racial categories are originally individual indicators. I began by identifying all individuals identified as only one racial category and those identified in the data as having two or more races. I then also collapsed the ethnicity category such that individuals labeled as White represent those in the data labeled as White non-Hispanic. For analysis purposes, I created a set of dummy variables where each student is only represented once across these variables. White was used as the comparison group. In some cases, to simplify analyses, I used the percentage of minoritized students (or the percentage of non-White and non-Asian students).

Special Education Status. This variable was dichotomous, with 1 representing students who received special education services and 0 for all other students.

School Characteristics.

Grade Levels. This variable was only used in descriptive analyses, not inferential analyses, as those inferential analyses focus only on one grade level. Elementary schools served students in grades K–5, middle schools served students in grades 6–8, and high schools served students in grades 9–12. In this analysis, I grouped grade levels in non-mutually exclusive categories such that K–8 schools or 6–12 schools would belong to multiple groups.

School Location—Urbanicity. This categorical variable was drawn from the CCD. The original CCD variables are collapsed into four major categories defined by the National Center for Educational Statistics: urban, suburban, town, and rural. The NCES definition combines measures of population and distance from a census-designated metropolitan area. Past research has documented how teacher attrition varies systematically based on school urbanicity (Ingersoll, 2001; Nguyen, 2020).

School Size. Schools were grouped into three size categories following Loveless (*2017 Brown Center Report on American Education*, n.d.): small schools (enrollment between 1–330), medium schools (enrollment between 331–1,300), large schools (enrollment above 1,301). Medium schools were used as the comparison group. School sizes result in differing organizational structures. The scale of these schools has the potential to influence student achievement systematically (Egalite, 2016).

Student Population Variables. In addition to including variables that capture individual student characteristics, school-year level aggregates of many individual variables were included to capture observable features of the school environment. Each variable represented the school's composition of these variables included at the student level. These variables were included at the school-year level to help account for the unequal distribution of students and control for these factors that research documents influence both student achievement (Eren, 2017; Hanushek et al., 2000; Hanushek et al., 2003) and teacher attrition (Allensworth et al., 2009; Feng, 2010).

Teacher and Staff Variables. In addition to other school variables, I also included variables that control for the composition of teachers and staff at each school. MLDS includes information on teacher race, license pathway[2], certification type[3], teacher preparation program

[2] License pathway is an indicator for teachers who ever held an alternative license in Maryland (aka Resident Teacher Certificate).

[3] Certification types are used to identify teachers in schools teaching under a conditional certification. This certification is only granted when the school cannot fill the position with a traditional or alternatively licensed teacher

state[4], teacher experience[5], and degree type[6]. Scholarship indicates each of these measures is associated with differing patterns of teacher attrition (Clotfelter et al., 2007; Goldhaber & Cowan, 2014; Ingersoll et al., 2022; Kirksey, 2024; Papay et al., 2017; Redding & Smith, 2016; Seftor & Mayer, 2003), and thus I included each as controls in inferential analyses.

Principal New to Role. This was a dichotomous variable, with 1 indicating that the principal was new to the role and 0 representing that the principal has been in that role for over a year. This value only indicates if the principal was new to the role and does not account for individuals who may have worked in other capacities in the building before assuming the role of the principal. Principal turnover has been linked to reduced student achievement and increased teacher turnover (Bartanen et al., 2019), thus this variable seeks to control for this factor.

Student-Teacher Ratio. This variable was calculated as the number of students in the building over the number of teachers in the building. This measure stands in for class size, a factor that teachers often cite for their attrition from schools (Isenberg, 2010; Loeb et al., 2005).

Methods and Analysis

This section introduces the methods and analyses used to investigate the assumptions and hypotheses outlined earlier. Each assumption was aligned with a distinct set of tests and data arrays that either support or contradict the assumptions. In this analysis, the first two assumptions (A1 & A2) were primarily exploratory rather than confirmatory. Thus, findings from the analyses conducted under A1 and A2 do not confirm or reject those assumptions but rather inform subsequent analyses. Thus, each assumption builds upon the insights gained from

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[4] Teachers are grouped into in-state and out-of-state prepared.

[5] Teacher experience is used to identify teachers with less than three years of experience, denoted as novice teachers.

[6] Degree type is used to identify teachers with a master's degree or higher.

findings from previous assumptions and produces adjustments to the approaches described in the section below. I outline the tests conducted and how each test contributes data to support or challenge the assumption. This iterative approach ensures a thorough and data-driven investigation.

A1: Some Degree of Teacher Attrition is Typical within a School. This assumption's analysis focuses on examining the distribution of attrition rates across schools. Testing this assumption begins by determining common attrition patterns across schools over time. I established a range of typicality for 1-year attrition and then established a similar set of ranges for other attrition measures. Of primary concern at this stage of the analysis was establishing a zone of typicality, with the expectation that a useful metric, in addition to being driven by associations with harmful outcomes, would also represent a small subset of schools.

I conducted a series of descriptive statistical analyses to assess the assumption of typical teacher turnover in schools. This analysis focused less on predefined criteria for typicality and more on values that represent typicality on a surface level. These descriptive analyses captured variation within and across time, arraying the options for typicality.

First, I calculated the single-year attrition rate for each school. Next, I examined the distribution of 1-year attrition rates across schools within each school year. To examine this distribution, I created frequency histograms for each school year. These displays show the shape of the distribution within any given school year and how and if these distributions differ from year to year. Examinations of these distributions show which rates are more and less common across schools.

Next, I examined different measures of central tendency and other key percentile thresholds, including the mean, median, 5th, 25th, 75th, and 95th percentile across school years.

I displayed these values on a line graph to show the trend over time. This trend and the highs and lows of these values serve as a preliminary estimate of a range of typical attrition.

In addition to analyzing different measures of central tendency across all schools in the state, I also explored whether student- and school-level characteristics are associated with variations in average school-level attrition. This analysis helped determine whether typicality varies across specific contexts or student groups and laid the groundwork for inferential analyses linking attrition to student outcomes (A3). This step ensured a more nuanced understanding of the relationships at play by identifying key student- and school-level factors to account for. Given that teacher staffing patterns differ across grade levels (elementary, middle, and high school; Carver-Thomas & Darling-Hammond, 2017; Marinell et al., 2013), student achievement, and student racial composition (Allensworth et al., 2009; Guarino et al., 2011; Loeb et al., 2005), I further disaggregated these yearly rates by groupings of each feature. I created line graphs and examined these visuals in addition to the trends for the aggregate measures over time, looking for areas of overlap between and across school types.

Finally, as prior analyses look at school features in isolation, many of which occur in schools concurrently, I created a model that predicts school attrition based on prior year school-level variables.

$$\overline{\mathrm{TA}}_{\mathrm{s,t-n}} = \beta_{0j} + \beta_1 \mathrm{X}_{\mathrm{s(t-n-1)d}} + \varphi_{\mathrm{t}} + \theta_{\mathrm{d}} + \varepsilon_{\mathrm{s}}$$

In Equation 1, $\overline{\mathrm{TA}}_{\mathrm{s,t-n}}$ is the average teacher attrition rate where t-n represents the duration (n can take values 1-6), $\beta_4 X_{s(t-n-1)d}$ is a vector of prior year school characteristics, which also includes aggregates of all student characteristics, φ_{t} is a school year fixed effect, θ_d is a district fixed effect, and ε_s is the school clustered standard error term. The results from this regression model demonstrate the predicted teacher attrition rate controlling for various school features. I centered all continuous variables so that the interpretation of the constant represents a school with the average composition of each variable.

I replicated these analyses for 3-year average attrition and 3-year attrition rates to show how these measures may change based on their differing durations.

Areas of overlap across school years and between disaggregated groups serve as the primary indicator of typicality. The intent would not be to establish a single value of typicality but rather an initial threshold of typicality that will be further examined for its policy relevancy under A3. Across all typical measures, this analysis assumes that a phenomenon should not be considered typical if only a minority of schools would meet the definition. I identified confluence across different analyses above that capture most schools observed.

A2. Over Time, Schools Experience Different and Distinct Forms of Longitudinal Attrition.

One of the goals of this project is to investigate the impact of longitudinal attrition in schools and to recognize that various forms of this turnover may exist. Like A1, I did this by examining descriptive statistics; however, while A1 focuses on examining patterns across schools, A2 focuses on examining the existence of distinct patterns within schools over time. To examine this assumption, I conducted a series of analyses focusing on how individual schools' attrition patterns vary over time. These analyses included exploring how much variation schools experience over multiple years and how staff departures accumulate over time.

I began by generating spaghetti plots that chart each school's 1-year attrition rate between 2009–2019. I used these visuals to examine how much variation schools experience from year to year. I grouped school year observations in groups that help to interpret common patterns within schools. I created additional split plots and overlaid plots of these groups to examine patterns within and between these school groupings. This set of analyses aimed to examine if there is preliminary evidence to suggest that some subsets of schools experience sustained periods of high attrition or chronic attrition while other schools do not.

I also used spaghetti plots to create visuals that show how staff departures accumulate over time. Analyses of these visual data representations and the number of schools that fall into each relative category helped to demonstrate the actual presence of differing patterns rather than the theoretical existence of such schools.

While analyses of these individual school patterns helped to interrogate the existence of differing patterns, a separate set of analyses is needed to clarify the extent to which the constructs are distinct enough to justify separate analyses. To assess this overlap, I examined correlation coefficients within each group of multi-year measures proposed to analyze chronic attrition and cumulative attrition, as well as between the different groups of measures (e.g., 3-year average attrition rate correlation to 3-year attrition rate) to assess the extent to which these measures are meaningfully distinct. I also created scatter plots of a subset of these measure comparisons to assess the extent to which variation may be greater on one side of the distribution.

Taken together, this data provides insight into the discriminant validity of each proposed measure. While there are more complex ways to examine discriminant validity, these measures are generated from a single figure rather than an aggregate of multiple items or items with greater potential measurement error (for which other tests may be more appropriate; Rönkkö & Cho, 2022). Because of the unitary nature of these measures with minimal concern for measurement error, I choose to focus on basic correlations and examinations of scatterplots as a strategy that is sufficient to make an initial assessment of whether the proposed measures capture distinct constructs. This approach allows for an initial, straightforward evaluation of the degree to which each measure differs from others. I then further assessed the measures' distinctiveness by examining the associated student outcomes under A3.

A3: Atypical Forms of Teacher Attrition Are Harmful to Students, and More Disruptive Forms of Teacher Attrition Will Be Associated With More Severe Negative Student Outcomes.

The first goal of this hypothesis is to examine the predicted one-year student outcomes associated with attending a school experiencing various longitudinal attrition measures to inform how to define each measure in terms of duration and intensity. While previous assumptions consider possible thresholds in terms of distinctiveness and frequency across school settings, the aim at this stage was to refine these thresholds based on their association with different intensities of harmful student outcomes. The points at which the intensity of the relationship shifts will indicate an appropriate threshold for that construct. I focused on measuring the outcome after one year of exposure to an existing longitudinal pattern. This consistent level of exposure offers a better comparison point, ensuring that any differences in the observed outcomes reflect the differing influence of sustained instability rather than variation in the timing or duration of exposure. Because I tested these assumptions across multiple student achievement outcomes, I sought to find the strongest point of convergence across settings and outcomes to inform the selection of appropriate thresholds to define each construct.

Furthermore, I assumed that different forms of attrition exist on a spectrum from most stable (episodic attrition) to least stable (chronic and then cumulative attrition) and that where each phenomenon falls on the spectrum is driven by three factors: rate, duration, and proportion of staff over time.

With the insights gained from inquiry into A1 regarding patterns of longitudinal attrition and A2 regarding typical attrition, I then focused on testing the third assumption: that atypical forms of teacher attrition are harmful to students and forms of teacher attrition associated with more instability will be associated with more severe negative student outcomes. This assumption builds a predictive validity argument where I assessed the validity of proposed measures based on the phenomenon's ability to predict a set of student outcomes.

I examined this relationship using a school value-added model (SVAM) to examine how school-level constructs predict current student outcomes, conditioning on prior student outcomes. I also used a multilevel modeling approach to account for the clustering of students within schools (Hox, 2010; Raudenbush & Bryk, 2002). I refined the model based on data gathered through analysis of A1 and A2 on the shape and range of key descriptives and examination of the inclusion of nonlinear terms described below.

The primary model I use for this analysis is as follows:

$$A_{istd} = \beta_{0j} + \beta_1 F(\overline{TA}_{s,t-n}) + \beta_2 A_{i,t-1} + \beta_3 X_{istd} + \beta_4 S_{std} + \varphi_t + \theta_d + u_{st} + r_{ist}$$

In Equation 1, A_{istd} is student outcome (math achievement or ELA achievement) for student *i* attending school *s* for one year in year *t* in district *d*, $\beta_1 A_{i,t-1}$ is the lagged student outcome, $\beta_2 X_{istd}$ is a vector of student characteristics, $\beta_4 S_{std}$ is a vector of school characteristics, which also includes aggregates of all student characteristics, φ_t is a school year indicator, θ_d is a district indicator, u_{st} is a random intercept for each school-year observation, and r_{ist} is the level-1 residual capturing the unexplained within-school-year variation. I included the teacher attrition variable $\beta_1 F(\overline{TA}_{s,t-n})$ as a flexible function of the different measures of school-level attrition, which includes both linear and nonlinear relationships.

The variables included in the equation are described above in the data variables section. In addition to those variables, this model included two additional controls for a school year and district fixed effect. I included a school year indicator to account for temporal trends that may affect both student outcomes and teacher staffing in each year. Finally, I added a variable for district fixed effects to account for district policies that could influence both predictors and outcomes.

The difficulty in modeling this relationship is that low-income and other historically marginalized students are sorted into specific types of schools, and as such, it is difficult to determine whether high attrition causes worse student outcomes or whether students with lower test scores happen to be sorted into schools with high attrition. I address this concern with a value-added approach that is conditioned on students' prior-year outcomes. I followed Ballou et al. (2004), Harris (2011), and Jackson et al. (2020) in defining VAMs broadly as statistical models that attempt to account for the unequal distribution of students within schools by adjusting for a student's prior outcomes. Including prior student outcomes helps to account for the nonrandom sorting of students to schools. Despite concerns about the validity of VAM in other settings, research suggests they retain strong predictive value to inform policy (Angrist et al., 2015; Jackson et al., 2020).

A related concern is the "self-reflection" problem: target students are not only influenced by the phenomenon of interest, but their own actions "reflect back" to influence the phenomenon (Manski, 1993). This concern is likely to inflate (in absolute value) the relationship between attrition and student outcomes because the same set of students shows up on the right- and left-hand side of the regression equation. To address this concern, I limited the student sample in this and future stages to sixth graders entering a new middle school for the first time. In this case, I would be concerned that features of or actions taken by the students could influence teachers to leave or stay; thus, the students themselves may both cause and be affected by teacher attrition. Scholars have suggested researchers address this bias by isolating the variation in the phenomena that is free from the influence of the reflection-induced variation (Bettinger et al., 2016). In this analysis, I created an out-of-sample attrition measure derived from the school years prior to a cohort of sixth graders joining the school. By limiting the analysis to cohorts of sixth graders in their first year at the school, I portioned out the influence of the sample from the outcome.

While this approach strengthens internal validity by addressing the self-reflection problem, it necessarily narrows the scope of inference. Because the analysis captures only the association between the school's prior attrition pattern on students during one year in a new school, the findings should be interpreted as estimating the initial exposure of longitudinal attrition, rather than the full accumulation of harm that might emerge over multiple years. As such, the results likely understate the broader consequences of persistent attrition for students who remain in unstable school environments over time. Conversely, these one-year outcome estimates are well aligned to compare to estimates of the impact of one year of attrition on student achievement (Henry and Redding , 2018; Ronfeldt et al., 2013; Sorenson and Ladd, 2020)

As mentioned previously, initial exploratory analyses of average school-level attrition rates indicate that an unexplained drop in attrition occurred in 2011. Since this drop represents an anomaly in the trends observed in the sample, I further limited the sample to the data used in inferential analyses from 2012–2019 so that the observed drop influences none of the attrition rates but that all measures could be calculated for these years.

Best practices in SVAM also inform this model. First, for SVAMs, it is important to include not only controls for individual student characteristics but also the school-level aggregates of these traits (see data descriptions for details on the specific covariates used in this model; Ehlert et al., 2014). While research generally suggests the use of two-step models in the calculation of school value-added (Ehlert et al., 2014; Harris & Larsen, 2023), in this case, because the dependent variable is a school outcome (school-level teacher attrition) rather than an individual school, I can include school-level aggregates in a one-step model.

I further improved their sensitivity through the inclusion of multiple lagged outcome covariates (Levy et al., 2023). The inclusion of multiple lagged outcomes is theorized to improve the model's sensitivity, as each previous year's outcome may have been influenced by a slightly different subset of unobserved variables. In this case, I included all three outcome variables of interest: math achievement, ELA achievement, and attendance as student-level controls.

As discussed in Chapter 2, theory suggests that there is cause to examine teacher attrition as a nonlinear function. To assess model fit I compared the primary linear model above for each attrition measure to those that include a squared term, a cubed term, and a natural log term. I began by running a set of models for each attrition construct including the linear and nonlinear terms. I compared the fit of each set of models model using the Akaike Information Criterion (AIC; Akaike, 1973). I used AIC as the primary indicator of model fit, and following Burnham and Anderson (2004), I calculated $\Delta_i = AIC_i - AIC_{min}$ and determined that $\Delta_i \leq 2$ have substantial support (evidence), those in which $4 \leq \Delta_i \leq 7$ have considerably less support, and models having $\Delta_i > 10$ have essentially no support.

I used the model refinement process to identify the strongest model at each duration and used those to examine differences across durations to identify thresholds for durations in terms of the number of years a pattern exists. At this stage, I compared coefficients related to different measures of turnover (e.g., 1-year attrition rate versus 2- or 3-year attrition rate) and student outcomes.

I then used the preferred models to compare the associations between each attrition measure and ELA achievement and math achievement. I expected that the coefficients relating cumulative attrition to student outcomes would be larger in absolute value than the coefficients relating chronic attrition to the same outcomes and that the coefficients relating chronic attrition to student outcomes would be larger than the coefficients relating to episodic attrition. To formally compare these estimates I implemented seemingly unrelated estimates (SUEST) tests (Mize et al., 2019) where possible. For the purpose of data-driven policymaking, I also compared coefficients within each construct but with different time frames to examine whether there are inflection points where attrition becomes increasingly harmful (or not). I provided both tables of regression coefficients produced by this analysis and graphed the average marginal effects of each model with 95% confidence intervals to show how student outcomes vary with the addition of an additional year to the school's average. This visual representation is helpful in assessing if there is a meaningful threshold for which outcomes accelerate or flatline. This visual examination should provide us with information that can guide us toward the selection of the number of years after which the associated harm is accelerated, indicating a logical benchmark for the constructs. In addition to examining the data itself, I used past research on annual (Ronfeldt et al., 2013) and longitudinal attrition effects (Sorensen & Ladd, 2020) on student achievement as additional referents.

I then followed the same processes outlined above while focusing on the intensity of the attrition forms. I used the same visuals and coefficients to examine the shape of the predicted outcomes to identify the point at which the intensity becomes more acute compared to other rates and to identify the point or range where attrition becomes associated with substantively more disruption. I intended this identified threshold to represent the point at which attrition becomes atypical, harmful, and worthy of policymakers' concern. These tests identified a preliminary threshold for the intensity and duration of each relevant attrition construct.

Chapter 4: Descriptive Findings for Assumption 1 and 2

Introduction

Chapter 4 presents findings for the first two assumptions guiding this study. Under each assumption, I analyze the data as outlined in Chapter 3, discuss the implications of these analyses to the field, and consider their utility to later stages of the analysis. A1 focuses primarily on descriptive statistics that capture patterns across schools over time, while Analysis of A2 focuses on descriptives that interrogate patterns within schools over time.

These analyses reveal that while most schools experience some attrition year over year, only a small subset of schools experience the most extreme forms. Additionally, while theory suggests three distinct constructs (episodic, chronic, and cumulative attrition), there is insufficient evidence to consider all three as distinct constructs. Instead, I focused on episodic and chronic attrition for analyses conducted under A3 in Chapter 5.

Assumption 1 Analyses

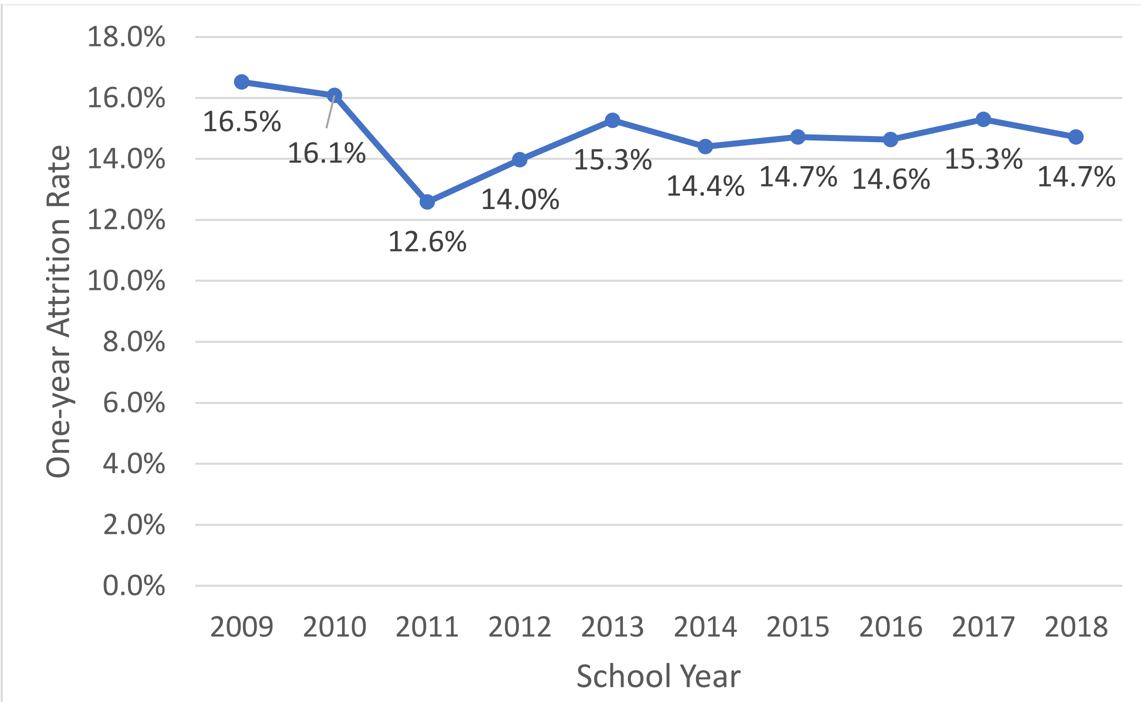
To investigate A1, I examined teacher attrition patterns across schools, including distributions, ranges, and central tendencies. Under this section I also explore potential typicality thresholds by modeling the relationship between attrition rates and prior year school features. These findings offer insight into the range of school experiences, and this analysis can speak to, as well as gain, additional insight into how various common attrition rates are within the sample data. I concluded inquiry into A1 by identifying minimum thresholds for typicality and exploring how these measures vary systematically across school types.

One-Year Attrition Rates Over Time

As shown in Figure 4.1, between 2009 and 2019 the average 1-year attrition rate was 14.9%, with a high of 16.5% in 2009 and a low of 12.6% in 2011. These patterns are well within

Figure 4.1

Maryland School-Level Attrition 2009–2019

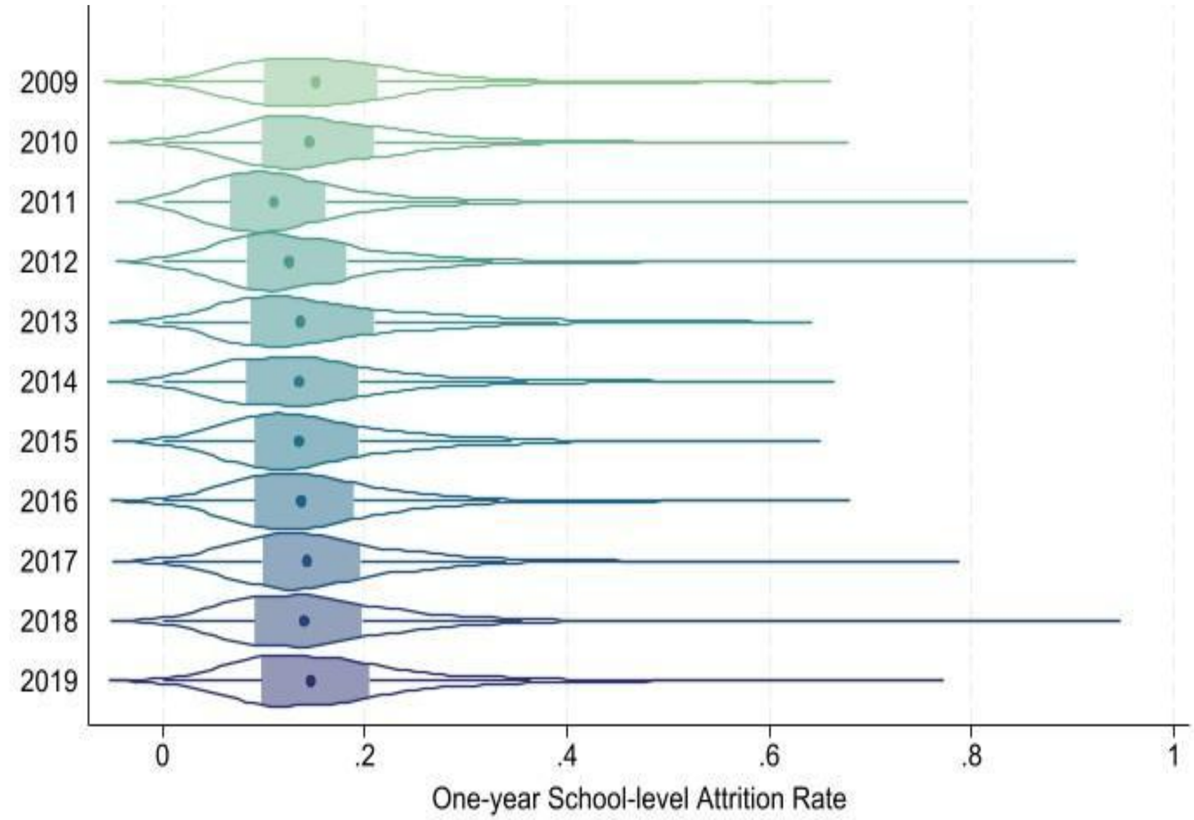


The graph displays the statewide average of 1-year attrition rates between 2009–2018.

the realm of research-documented rates, which estimate that, on average, schools in the United States lose around 12%–16% of teachers from their buildings annually (Goldhaber & Theobald, 2021; Ingersoll, 2001; Irwin et al., 2021; Sutcher et al., 2016), suggesting that Maryland is in line with previously studied settings for this measure. Figure 4.1 also shows that one year, 2011, appears to be an anomaly in terms of 1-year attrition. One could speculate as to the policy or economic factors that contributed to this dip in attrition, but since it is not the goal of this analysis to explain this particular anomaly, I excluded that year from analyses conducted under A3 in order to avoid bias introduced by the factors that contributed to this dip in attrition.

Figure 4.2

Distribution of 1-Year Attrition Rates 2009–2019

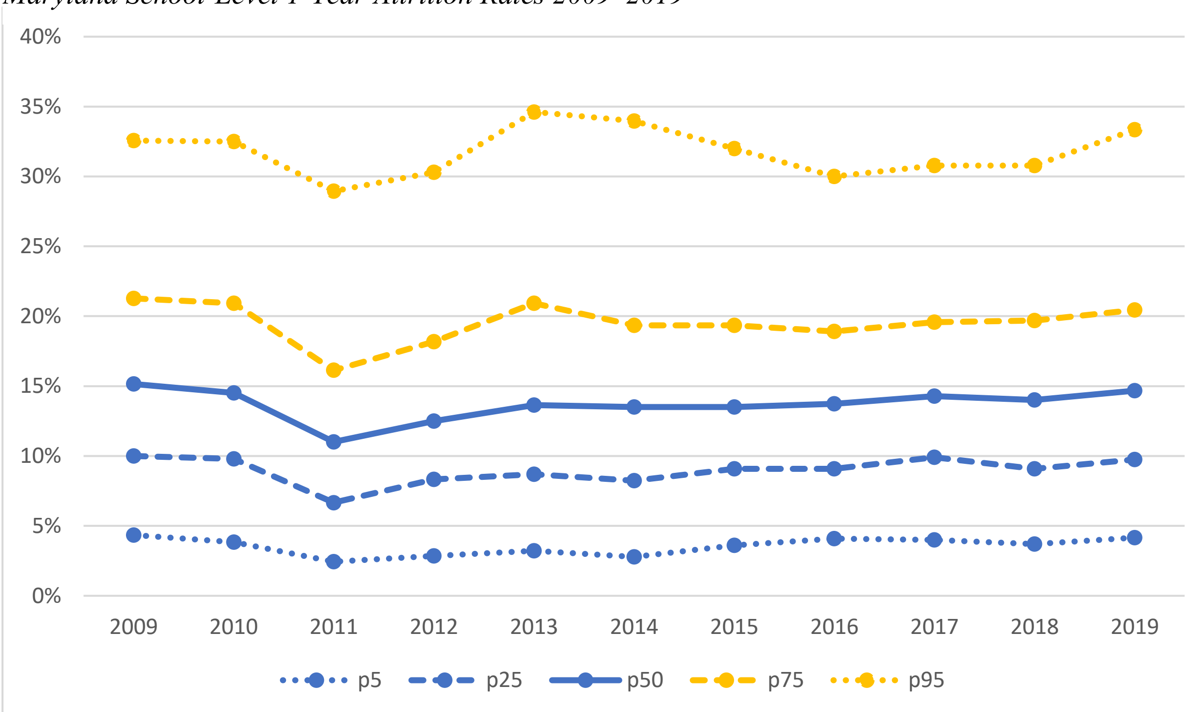


The dot in the center of each distribution represents the mean, the shaded portion represents the interquartile range, and the horizontal central line represents the 95% confidence interval

Figure 4.2 illustrates that the distribution of 1-year attrition rates is skewed to the right, with extreme values pulling the mean above the median. During this time period, the median or 50th percentile had a high of 15.2% in 2009 and a low of 11.0% in 2011. Furthermore, as shown in Figure 4.3, during this time period, the 75th percentile remains below 22%, and the 95th percentile below 35%, with the max ranging from 58.8% to 89.7%. Thus, while some schools experience particularly extreme elevated attrition rates, it appears that generally it is highly atypical (effecting less than 5% of schools per year) for schools to lose more than one third of

Figure 4.3

Maryland School-Level 1-Year Attrition Rates 2009–2019



This graph displays the min, max, and percentile thresholds for the 5th, 25th, 50th, 75th, and 95th percentiles for 1-year attrition rates between 2009 and 2019.

their teachers in any given year. However, it is also important to note that despite these extreme measures being somewhat rare, half of schools lose 14%–15% or more of their teachers annually.

Figure 4.4 shows how disaggregating 1-year attrition rates by school income and racial composition reveals disparities consistent with prior research (Papay et al., 2017; Redding & Henry, 2018). Schools with above-average percentages of students eligible for free and reduced-price meals (FARMS) and above-average percentage of minoritized students have higher median attrition rates. During this time period the median for schools with above-average FARMS populations ranged between 18.9% in 2009 to 12.8% in 2011, while the median for other schools with average FARMS populations ranged between 13.3% in 2009 to 9.7% in 2011. Similarly, the median for schools with above-average percentage of minoritized students ranged from 19.0% in

Figure 4.4

Median Maryland School-Level 1-Year Attrition Rates by Student Demographics 2009–2019

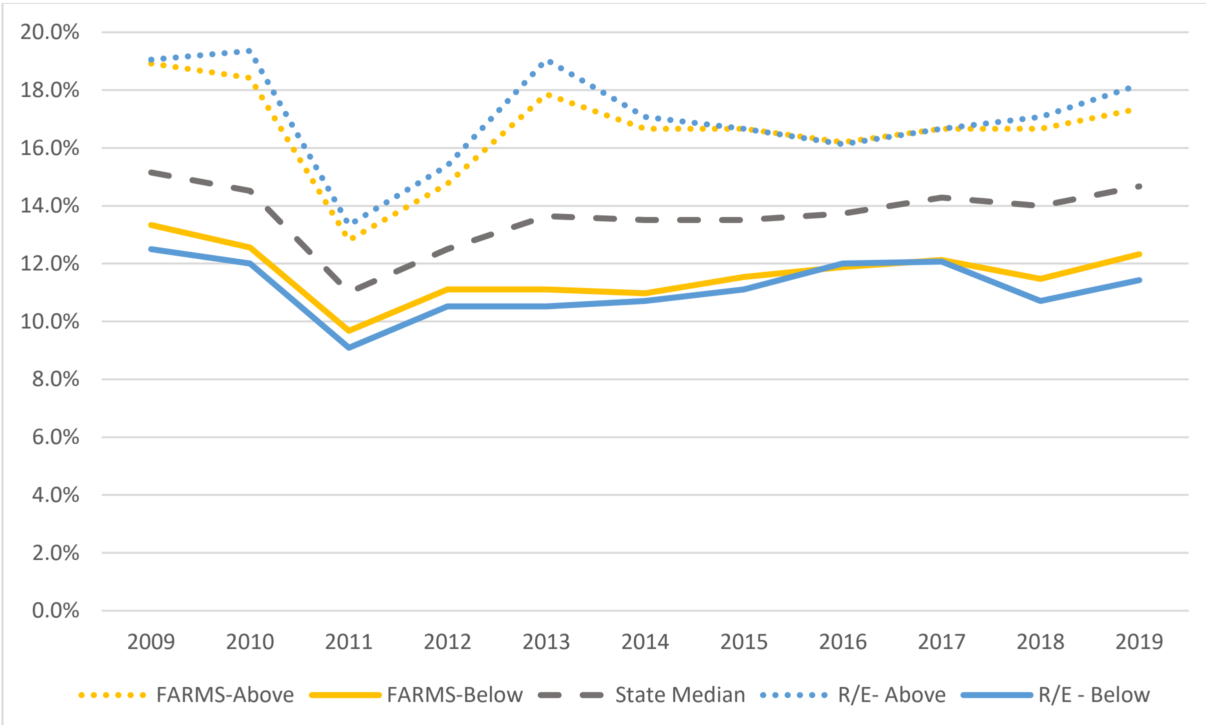


Figure 4.5

Median Maryland School-Level 1-Year Attrition Rates by School Level 2009–2019

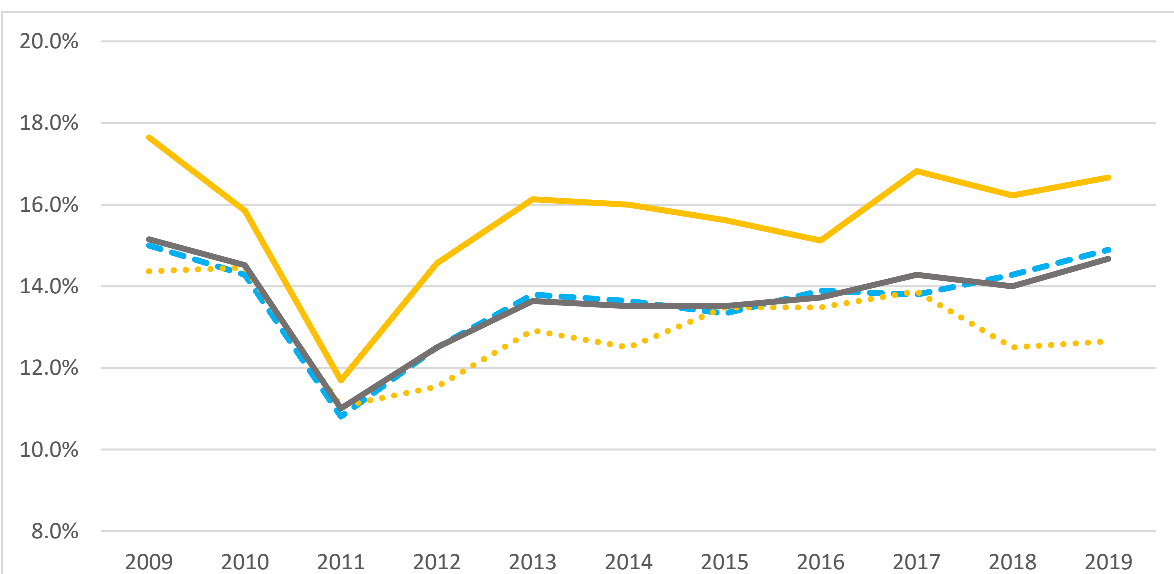


Figure 4.4 displays the median 1-year attrition rates by school poverty level and minoritized student populations between 2009 and 2019.
Figure 4.5 displays the median 1-year attrition rates by school level between 2009 and 2019.

2009 to 13.3% in 2011, while the median for other schools ranged from 12.5% in 2009 to 9.1% in 2011. These patterns, while not identical, strongly mirror each other, which makes sense given the high correlation between school racial and ethnic composition and socioeconomic status in Maryland with a minoritized student population below the state average ranged from 12.5% in 2009 to 9.1% in 2011. As evidenced by Figure 4.4, these patterns, while not identical, strongly mirror each other, which makes sense given the high correlation between school racial and ethnic composition and socioeconomic status in Maryland schools (WYTOP News, 2020). Additionally, from this visual it appears that while schools on both sides of these dichotomies experienced some variation in attrition rates during this period, schools with high FARMS or minoritized student populations saw bigger increases in years where the state average rose. During these years, the gap in attrition rates between high and low schools grew, suggesting that these schools may be a greater force in driving statewide trends. These patterns emphasize that typicality varies consistently by school types.

Data from Maryland shows some interesting patterns not documented in prior research on attrition patterns based on school levels. Figure 4.5 shows that middle schools experienced the highest median attrition rates during this period, with elementary and high schools experiencing lower rates. During this period, schools serving high school students experienced the lowest attrition rates, ranging from a low of 11.1% in 2011 to a high of 14.5% in 2010. Conversely, during this period, schools serving middle school students experienced the highest rates, ranging from a low of 11.7% in 2011 to a high of 17.6% in 2009. Schools serving elementary students most closely mirrored the statewide median pattern, with 1-year median attrition rates ranging from 10.8% in 2011 to a high of 15.0% in 2009. This observation is particularly important to consider as I analyze data under A3 due to the proposed approach that limits the sample to schools that serve middle school students. As I consider relevant benchmarks, it will be important to consider that those schools' attrition rates are on average 1%–2% percentage points

Figure 4.6

Median Maryland School-Level 1-Year Attrition Rates by Student Achievement 2009–2019

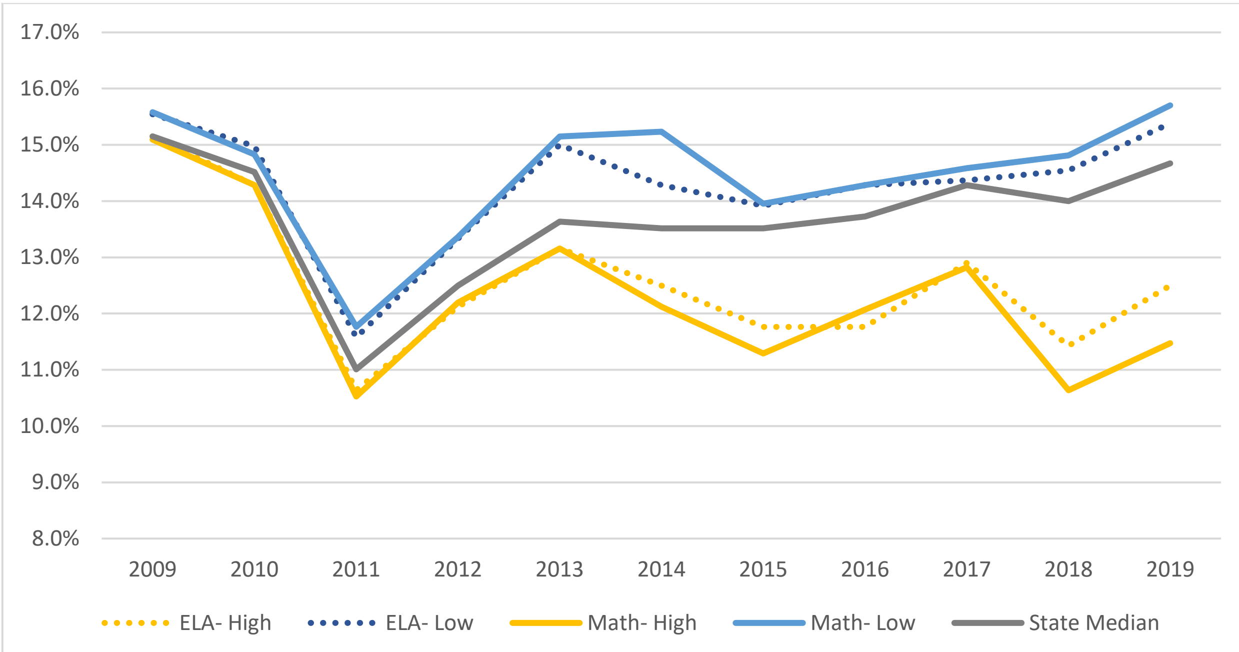


Figure 4.6 displays the median 1-year attrition rates by student achievement level between 2009 and 2019.

higher than other school types.

Figure 4.6. shows median attrition rates disaggregated by ELA and math achievement. Low-achieving schools[7] have attrition rates consistently above the state median and higher than the state average. Between 2009 and 2012, the gap between high- and low-achieving school attrition rates is relatively small, generally less than one percentage point. This gap grows; by

[7] Low-achieving schools are those with proficiency rates below the state average as measured by the state assessment that year.

2018 and 2019, there is a 3-percentage-point differential between high- and low-achieving schools.

Looking at these patterns in isolation can give a sense of the range of common attrition rates by these categories but may oversimplify the picture. Combining a range of school features in a single regression equation can better show the most significant factors associated with different attrition rates. The results of this combined equation displayed in Table 4.1 show that after controlling for a range of prior-year school, teacher, and student demographics, as well as variation across school years, the average school in Maryland experiences a 14.5% 1-year attrition rate slightly above the pooled media of 1-year attrition rates for the sample. Middle schools are associated with a 0.76-percentage-point-higher rate than elementary schools, while high schools are associated with a 3.22-percentage-point-lower rate. Compared to small schools, medium-sized schools are associated with a 1.00-percentage-point lower 1-year attrition rate. Schools with new principals and those receiving Title 1 assistance were associated with increased 1-year attrition rates, while the student–teacher ratio was associated with a small but significant decrease.

Among the teacher characteristics, the strongest predictors are the percentage of novice teachers. Compared to a school with no novice teachers, schools with 100% novice teachers were associated with a 13.6 percentage point increase in 1-year teacher attrition. The percentage of non-White teachers and teachers with conditional certificates is associated with higher attrition rates, while the percentage of teachers with a master's degree or higher was associated with lower attrition rates. Other teacher characteristics, including alternative certification and out-of-state preparation, were not statistically significant predictors of 1-year school-level teacher attrition.

Table 4.1
School-Level Predictors of 1-Year Attrition Rates

VARIABLES	Beta	Standard error
Constant	0.145***	(0.00369)
School features		
Urbanicity[8]		
Urban	–0.00182	(0.00314)
Rural	–0.00152	(0.00251)
Town	–0.00493	(0.00391)
New principal	0.0149***	(0.00185)
Grade levels[9]		
Middle school	0.00760**	(0.00355)
High school	–0.0322***	(0.00397)
Elementary/middle school	–0.00120	(0.00611)
Middle/high school	–0.0261***	(0.00886)
Elementary/middle/high school	–0.0601***	(0.0140)
Title 1 Status[10]		
Targeted assistance	0.00947**	(0.00429)
School wide	0.00782***	(0.00302)
School size[11]		
Medium size	0.0100***	(0.00341)
Student–teacher ratio	-0.00779***	(0.000576)
Teacher population		
Percentage of novice teachers	0.136***	(0.0132)
Percentage of teachers with Masters or higher	–0.0435***	(0.00884)
Percentage of non-White teachers	0.0947***	(0.0104)
Percentage of teachers out-of-state prepared	0.00175	(0.0138)
Percentage of teachers prepared through alternative certification	0.0562	(0.0350)
Percentage of teachers with conditional certification	0.0937***	(0.0306)
Student population		
Percentage of students with free and reduced-price meals	–0.0196***	(0.00604)
Percentage of students with disability	–0.0261	(0.0186)
Percentage of student English learners	–0.0392***	(0.0112)
Average student days absent	0.00111***	(0.000305)
Percentage of minoritized students	0.0143*	(0.00816)
Percentage of students female	0.0345*	(0.0207)
Percentage students proficient or above ELA	0.0607***	(0.0196)
Percentage of students proficient or above math	–0.0927***	(0.0190)
Observations	13,291	
R-squared	0.328	

Model predicts 1-year average attrition rates (episodic attrition measure) from school features. School-year clustered standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1

[8] Suburban schools serve as the reference category
[9] Elementary schools serve as the reference category.
[10] Non-Title 1 schools serve as the reference category.
[11] Small schools serve as the reference category.

Student population descriptives are also significant predictors of teacher attrition the following year. Math proficiency, the percentage of English learners, and the percentage of students eligible for free and reduced-price meals are associated with lower attrition rates. In contrast, higher student absences, and ELA proficiency are associated with higher attrition rates.

Other student characteristics were not associated with statistically significant differences. Taken together, it appears that most schools and school types experience 1-year attrition rates at or below 15%. As I considered significant thresholds under testing for A3, this value was important to keep in mind. While the analysis in A3 is primarily driven by associated negative outcomes, given the policy-relevant frame of this analysis, it is also important to set a threshold that does not capture too many schools to provide actionable information for policymakers.

Furthermore, while this analysis has provided a starting point to identifying typicality, this task is complicated due to the substantial heterogeneity amongst 1-year attrition rates. Several school, student, and teacher characteristics are associated with this measure of attrition, but the direction of these relationships remains unclear, as other unaccounted factors may influence both. Regardless of the underlying causes, the primary analyses of A3 instead focus on understanding the impact of attrition on student outcomes.

Multiyear Average Rates (Chronic Attrition) and Multiyear Attrition Rates (Cumulative Attrition) Over Time

In addition to examining 1-year attrition rates across schools, I examine multiyear average rates (2- to 6-year average rates – measures aligned with chronic attrition) and multiyear rates (2- to 6-year average rates – measures aligned with cumulative attrition) across schools over time.

I began by looking at the 1-year rates and 2- to 6-year average measures. As these measures are multiyear averages, variation is reduced, as one might expect. As Figure 4.7 shows, each

Figure 4.7

Density of 1- to 6-Year Average Attrition Rates (Chronic Attrition)

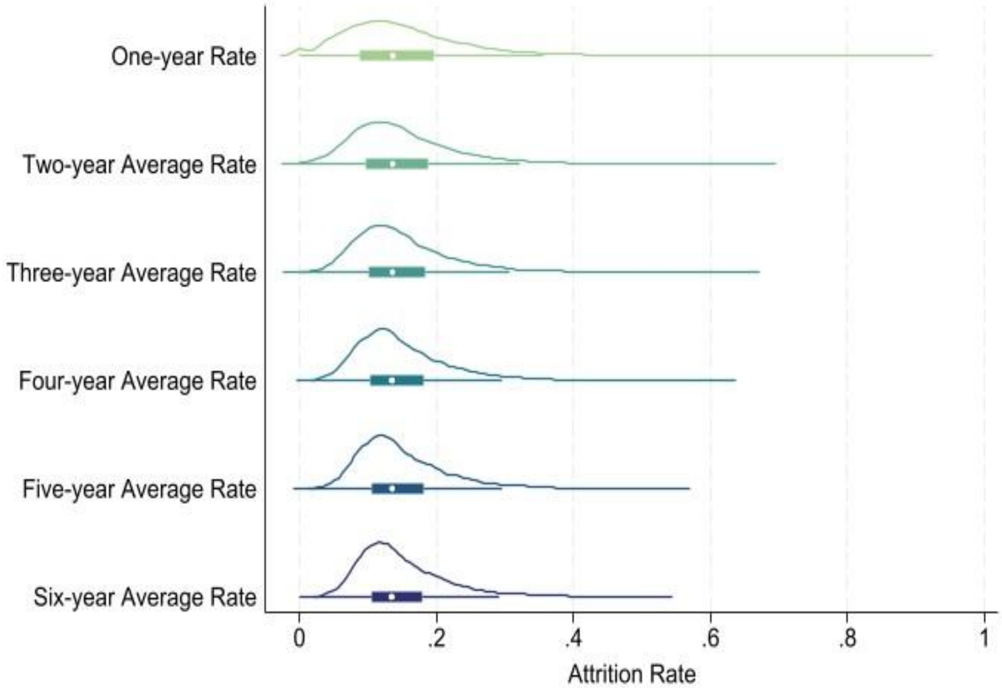
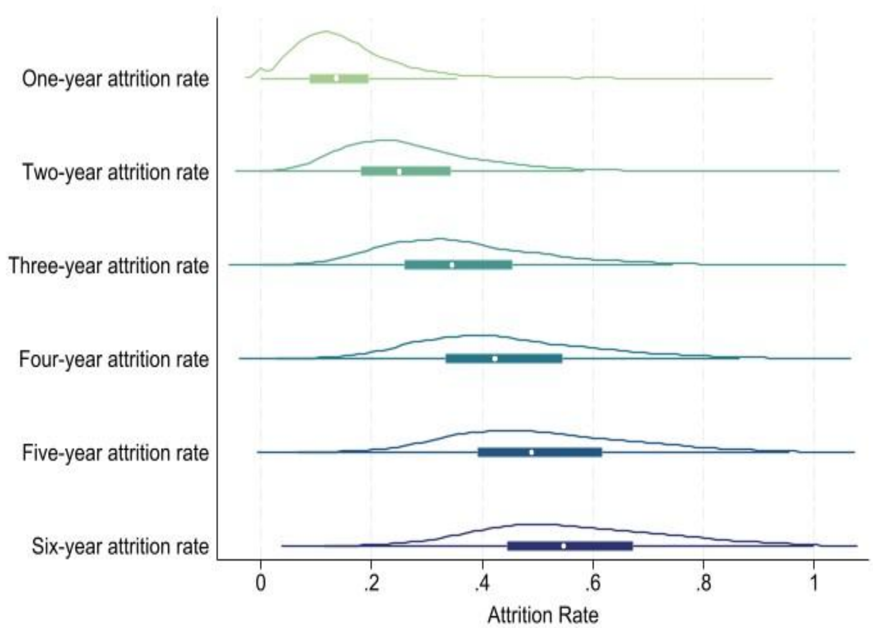


Figure 4.8

Density of 1- to 6-Year Attrition Rates (Cumulative Attrition)



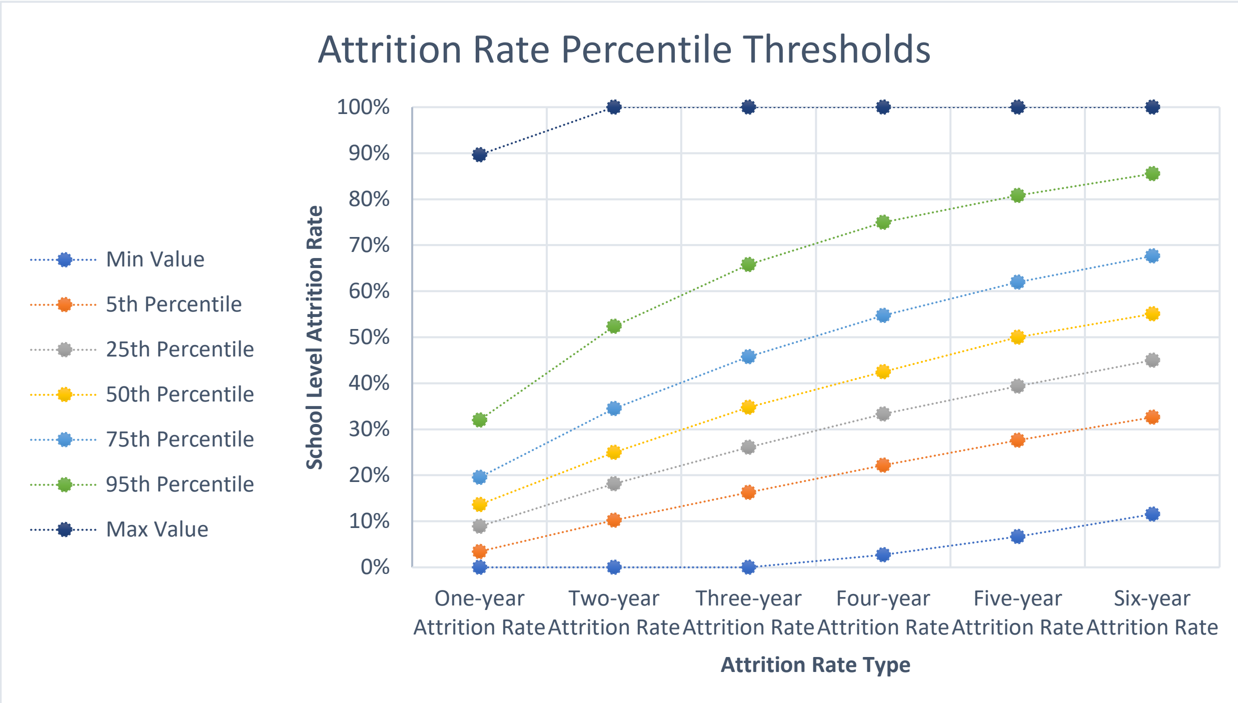
The dot in the center of each distribution represents the mean, the shaded portion represents the interquartile range, and the horizontal central line represents the 95% confidence interval additional year, the distribution includes less variation, with more observations falling closer to the mean. The median of the longer-term measures shifts closer to the mean, resulting in slightly more normal distributions. When looking across measures, the mean does not shift dramatically; instead, it pulls in the tail, resulting in fewer extreme values. The pooled mean for each measure is as follows: 1-year attrition rate is 15.1%, 2-year to 5-year average rate is 14.9%, and 6-year average rate is 14.8%.

The distribution of the 1- to 6-year rates shows much more variation than the 1- to 6-year average rates. Each additional year produces a distribution with a greater range and a flatter distribution, as shown in Figure 4.8. The pooled mean increases with the addition of each additional year: 1-year attrition rate is 15.1%, 2-year rate is 27.5%, 3-year rate is 37.0%, 4-year rate is 44.8%, 5-year rate is 51.2%, and 6-year rate is 56.6%.

Examining key percentiles more closely offers additional insight into how the distributions of these measures differ. As shown in Figure 4.9 the addition of each year of data generally increases the value for each of the percentile thresholds (max value—top dark blue line, 95th percentile—green line, 75th percentile—light blue line, 50th percentile—yellow line, 25th percentile—gray line, 5th percentile—orange line, and min value—royal blue line). In particular, it is useful to examine the gap between the max values (indicated by the dark blue line) and the threshold for the 95th percentile (indicated by the green line). There is a large gap between the 95th percentile and the max values. For example, while the max value for 3-year attrition rate is 100%, the threshold for the 95th percentile is 65%, implying that schools experiencing rates this high are extremely rare. While the gap between these two points diminishes as the measures encompass additional years, even for the 6-year attrition rate, there is a 15 percentage point gap

Figure 4.9

Attrition Rate Percentile Thresholds Pooled 1- to 6-Year Attrition Rates (Cumulative Attrition)



between these two points. Conversely the gap between the minimum value and the 95th percentile grows with the addition of each year to the measures. While at least one school in the sample experienced no attrition for three years, as the fifth percentile for 3-year attrition is 16.2%, ninety-five percent of school year observations experienced 3-year attrition rates above this point.

The variation across both the distribution and measures of central tendencies of these multiyear rates raises an important issue for comparability across the models proposed under A3. As each of these rates has a unique distribution, direct comparison of raw rates could represent differing points within each metric's distribution. Instead, using a relative scale (such as standard deviations) to conduct these comparisons is important. By standardizing the scale of these measures, I can account for these differences in distribution shape, ensuring more meaningful

This graph displays the movement of the min, max, and percentile thresholds for the 5th, 25th, 50th, 75th, and 95th percentiles across the measures of cumulative attrition (1- to 6-year attrition rates).

comparisons based on relative positioning, which can offer better insight into typicality within each measure.

Examining the median 3- and 6-year average rates and median 3- and 6-year rates in greater detail offers insight into how typicality may differ compared to 1-year rates. The median 3-year average attrition rate ranged from a low 12.6% in 2013 to a high of 14.4% in 2019, a slightly narrower range compared to 1-year attrition rates. The median 3-year attrition rate ranged from a low of 31.6% in 2013 and 37.4% in 2019. These values are over double the median 1-year school-level attrition rates observed. This data also shows that over the course of three years, over half of schools in Maryland lost a third of their teaching staff.

Turning to the even longer duration of six years, the median 6-year school-level attrition rates reveal that by Year 6 half of schools have lost over 50% of their teachers, ranging from a low of 53.3% in 2015 to a high of 56.7% in 2019. That means that by the time a kindergartener gets ready to transition into sixth grade, half of the teachers that worked at that school when they began attending would no longer be working there. At the same time, these figures represent a relatively high rate of staff instability. The difference between the 3-year and 6-year rates indicates that while attrition accumulates over time, the accumulation rate slows over time, with fewer teachers from the original cohort departing in each successive year.

Furthermore, the highs and lows of both 3-year measures (3-year average rate and 3-year rate) occurred in the same year, providing some preliminary evidence that there may be some alignment between these two measures. I examined this further under the analyses for A2.

Examining disaggregated rates over time by school type in Figures 4.10 and 4.11 again reveals almost identical patterns to those noted for other attrition measures. Since the observed patterns—higher attrition rates in schools serving more minoritized students, economically

Figure 4.10

Maryland School Level 3-Year Average Attrition Rates by School Type 2011–2019 (Chronic Attrition)

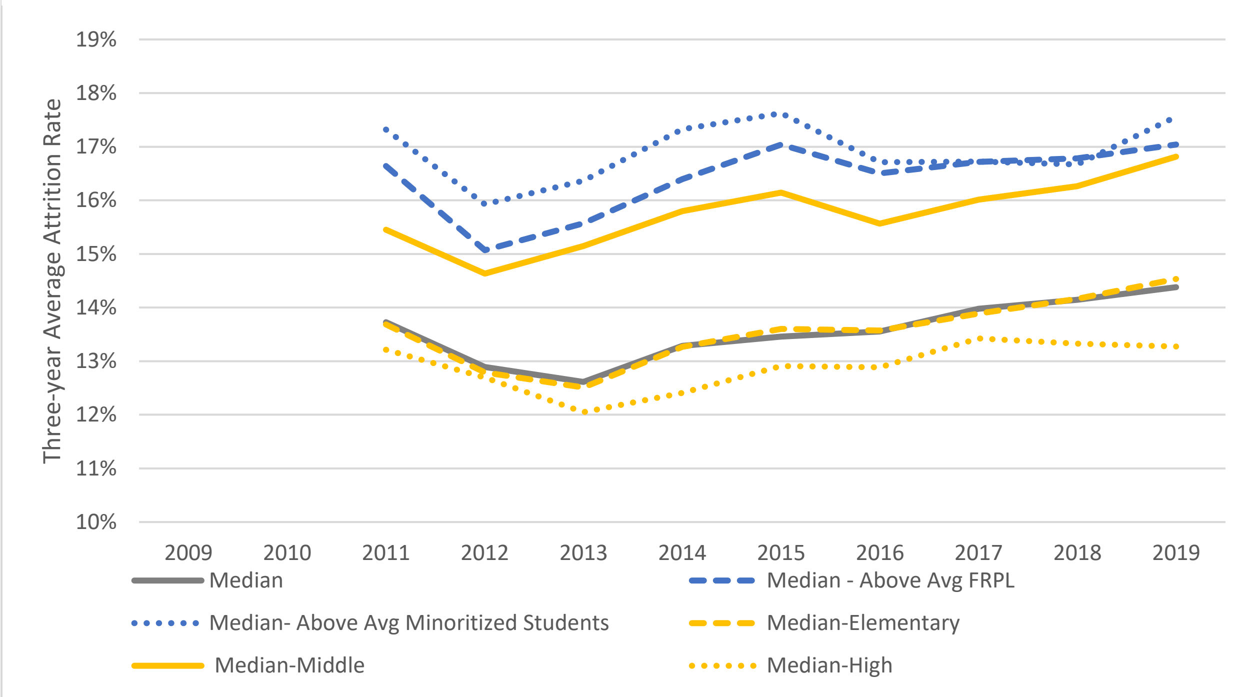


Figure 4.11

Maryland School Level 3-Year Attrition Rates by School Type 2011–2019 (Cumulative Attrition)

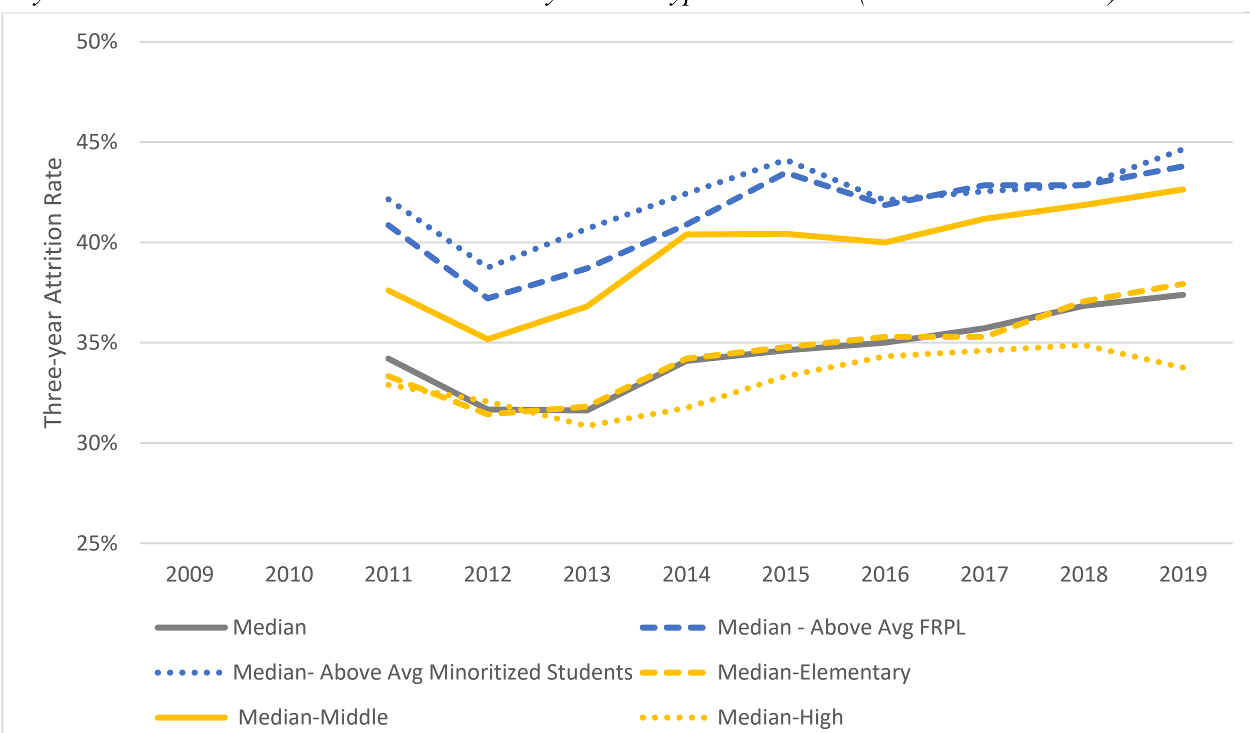


Figure 4.10 displays the median 3-year average attrition rates by school type between 2009 and 2019. Figure 4.11 displays the median 3-year attrition rates by school type between 2009 and 2019.

disadvantaged students, and middle schoolers—are consistent across multiple measures and over time, failing to account for them in statistical models could lead to biased conclusions.

Table 4.2 and 4.3 displays results of models that use a school's features to predict future attrition patterns. In many cases these models predict similar patterns as those described previously for 1-year attrition rates. While the magnitude of the relationships change slightly, elementary/middle/high schools, student–teacher ratio, percentage of teachers with a master's degree, percentage of students who are English learners, and percentage of students proficient in ELA and proficient in math are associated with statistically significant reductions in 2- to 6- year average attrition rates; and new principals, medium-size schools, the percentage of novice teachers, the percentage of non-White teachers, and the average number of student absences are associated with statistically significant increases in the 2- to 6-year average attrition rates.

In other places some predictors that were significant predictors (middle schools, Title I status, etc.) are not significant predictors for measures that include more years this appears to be driven by the reduction in the number of observations available for the rates that include more years as the coefficients do not change substantively. Despite some variation and shifts, no predictors change the direction of the relationship. The models that predict 2- to 6-year average attrition follow the same pattern where the majority of predictors remain significant in the same direction as for 1-year attrition and a subset of others become not significant. Emphasizing the ways in which both the multiyear and multiyear average measures behave largely similarly. The variations, however, provide another reminder that even across similar measures the same schools' features do not always predict outcomes in the same way.

Turning back to the primary focus of these models, they predict that the average school experiences 2-year teacher attrition rates of 26.8%, 3-year teacher attrition rates of around

Table 4.2
School-Level Predictors of 1- to 6-Year Average Attrition Rates (Chronic Attrition Measures)

VARIABLES	1-year attrition rate	2-year average attrition rate	3-year average attrition rate	4-year average attrition rate	5-year average attrition rate	6-year average attrition rate
Observations	13,291	11,891	10,498	9,131	7,774	6,431
R-squared	0.328	0.425	0.483	0.525	0.553	0.575
Constant	0.145***	0.146***	0.149***	0.151***	0.153***	0.154***
	(0.00369)	(0.00368)	(0.00371)	(0.00373)	(0.00385)	(0.00391)
School features						
Urban	–0.00182	–0.00128	–0.000280	6.66e-05	–0.000425	0.000189
	(0.00314)	(0.00318)	(0.00326)	(0.00334)	(0.00338)	(0.00352)
Rural	–0.00152	–0.00148	–0.00114	–0.00117	–0.000896	–0.000631
	(0.00251)	(0.00239)	(0.00241)	(0.00243)	(0.00239)	(0.00237)
Town	–0.00493	–0.00524	–0.00478	–0.00470	–0.00477	–0.00470
	(0.00391)	(0.00373)	(0.00369)	(0.00363)	(0.00346)	(0.00336)
New principal	0.0149***	0.00985***	0.00744***	0.00549***	0.00539***	0.00472***
	(0.00185)	(0.00139)	(0.00129)	(0.00123)	(0.00120)	(0.00126)
Middle school	0.00760**	0.00999***	0.00891**	0.00687*	0.00795	0.00550
	(0.00355)	(0.00354)	(0.00369)	(0.00404)	(0.00494)	(0.00526)
High school	–0.0322***	–0.0352***	–0.0343***	–0.0348***	–0.0366***	–0.0385***
	(0.00397)	(0.00410)	(0.00420)	(0.00424)	(0.00469)	(0.00493)
Elementary/middle school	–0.00120	7.77e-05	0.00166	0.00278	0.00384	0.00326
	(0.00611)	(0.00621)	(0.00633)	(0.00667)	(0.00716)	(0.00753)
Middle/high school	–0.0261***	–0.0205**	–0.0169*	–0.0131	–0.0124	–0.0169
	(0.00886)	(0.00898)	(0.00925)	(0.00963)	(0.00995)	(0.0107)
Elementary/middle/high school	–0.0601***	–0.0479***	–0.0420***	–0.0424***	–0.0471**	–0.0504**
	(0.0140)	(0.0145)	(0.0142)	(0.0149)	(0.0186)	(0.0196)
Title 1—targeted assistance	0.00947**	0.0119***	0.00952**	0.00776*	0.00549	0.00109
	(0.00429)	(0.00426)	(0.00431)	(0.00426)	(0.00447)	(0.00446)
Title 2—school wide	0.00782***	0.00862***	0.00434	0.00360	0.00251	0.00249
	(0.00302)	(0.00301)	(0.00345)	(0.00352)	(0.00365)	(0.00378)
Medium size	0.0100***	0.00851**	0.00801**	0.00766**	0.00676**	0.00699**
	(0.00341)	(0.00339)	(0.00337)	(0.00335)	(0.00336)	(0.00336)
Student–teacher ratio	–0.00779***	–0.00502***	–0.00379***	–.00307***	–0.00224***	–0.00174***
	(0.000576)	(0.000515)	(0.000522)	(0.000521)	(0.000538)	(0.000541)

VARIABLES	1-year attrition rate	2-year average attrition rate	3-year average attrition rate	4-year average attrition rate	5-year average attrition rate	6-year average attrition rate
Teacher population						
Percentage of novice teachers	0.136***	0.116***	0.111***	0.108***	0.112***	0.107***
	(0.0132)	(0.0124)	(0.0119)	(0.0121)	(0.0127)	(0.0137)
Percentage of teachers with Masters or higher	–0.0435***	–0.0383***	–0.0337***	–0.0275***	–0.0273***	–0.0249**
	(0.00884)	(0.00888)	(0.00925)	(0.00970)	(0.00997)	(0.0102)
Percentage of non-White teachers	0.0947***	0.0868***	0.0789***	0.0754***	0.0741***	0.0739***
	(0.0104)	(0.0102)	(0.0105)	(0.0109)	(0.0113)	(0.0116)
Percentage of teachers out-of-state prepared	0.00175	–0.00518	–0.00560	–0.00858	–0.0115	–0.0133
	(0.0138)	(0.0133)	(0.0133)	(0.0136)	(0.0139)	(0.0143)
Percentage of teachers prepared through alternative certification	0.0562	0.112***	0.145***	0.154***	0.125***	0.115***
	(0.0350)	(0.0343)	(0.0328)	(0.0321)	(0.0333)	(0.0319)
Percentage teachers with conditional certification	0.0937***	0.0839***	0.0758***	0.0905***	0.0999***	0.0840***
	(0.0306)	(0.0279)	(0.0275)	(0.0266)	(0.0253)	(0.0256)
Student population						
Percentage of students with free and reduced-price meals	–0.0196***	–0.0158***	–0.00107	0.00520	0.00535	0.0100
	(0.00604)	(0.00610)	(0.00886)	(0.00892)	(0.00905)	(0.00914)
Percentage of students with disability	–0.0261	-0.0146	–0.0122	–0.00302	0.0107	0.0151
	(0.0186)	(0.0157)	(0.0174)	(0.0179)	(0.0204)	(0.0200)
Percentage of student English learners	–0.0392***	–0.0444***	–0.0464***	–0.0501***	–0.0339***	–0.0345***
	(0.0112)	(0.00973)	(0.0100)	(0.0101)	(0.0100)	(0.00966)
Average student days absent	0.00111***	0.00145***	0.00161***	0.00158***	0.00160***	0.00172***
	(0.000305)	(0.000354)	(0.000380)	(0.000370)	(0.000393)	(0.000396)
Percentage of minoritized students	0.0143*	0.0228***	0.0268***	0.0295***	0.0312***	0.0317***
	(0.00816)	(0.00784)	(0.00802)	(0.00820)	(0.00842)	(0.00858)
Percentage of students female	0.0345*	0.0104	0.00429	0.00927	0.0109	0.00699
	(0.0207)	(0.0200)	(0.0213)	(0.0225)	(0.0244)	(0.0250)
Percentage of students proficient or above ELA	0.0607***	0.0748***	0.0730***	0.0804***	0.0829***	0.112***
	(0.0196)	(0.0182)	(0.0173)	(0.0176)	(0.0208)	(0.0256)
Percentage of students proficient or above math	–0.0927***	–0.109***	–0.100***	–0.104***	–0.108***	–0.134***
	(0.0190)	(0.0178)	(0.0169)	(0.0165)	(0.0186)	(0.0230)

Models predict multiyear average attrition rates (chronic attrition measures) from school features. School-year clustered standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4.3
School-Level Predictors of 1- to 6-Year Attrition Rates (Cumulative Attrition Measures)

VARIABLES	1-year attrition rate	2-year attrition rate	3-year attrition rate	4-year attrition rate	5-year attrition rate	6-year attrition rate
Observations	13,291	11,891	10,498	9,131	7,774	6,431
R-squared	0.328	0.429	0.481	0.504	0.517	0.518
Constant	0.145***	0.268***	0.370***	0.454***	0.525***	0.581***
	(0.00369)	(0.00634)	(0.00763)	(0.00836)	(0.00907)	(0.00950)
School features						
Urban	–0.00182	0.00310	0.00488	0.00544	0.00376	0.00542
	(0.00314)	(0.00564)	(0.00746)	(0.00879)	(0.00975)	(0.0106)
Rural	–0.00152	–0.00257	–0.000705	–0.00196	–0.00541	–0.00607
	(0.00251)	(0.00411)	(0.00551)	(0.00657)	(0.00721)	(0.00782)
Town	–0.00493	–0.00817	–0.00737	–0.00805	–0.0117	–0.0137
	(0.00391)	(0.00673)	(0.00880)	(0.0102)	(0.0107)	(0.0114)
New principal	0.0149***	0.0175***	0.0159***	0.0131***	0.0139***	0.0110***
	(0.00185)	(0.00238)	(0.00272)	(0.00291)	(0.00303)	(0.00326)
Middle school	0.00760**	0.0266***	0.0287***	0.0245**	0.0272**	0.0243*
	(0.00355)	(0.00633)	(0.00802)	(0.00960)	(0.0123)	(0.0140)
High school	–0.0322***	–0.0569***	–0.0641***	–0.0671***	–0.0658***	–0.0649***
	(0.00397)	(0.00688)	(0.00866)	(0.00963)	(0.0111)	(0.0119)
Elementary/middle school	–0.00120	0.00234	0.00902	0.0109	0.0121	0.0102
	(0.00611)	(0.0103)	(0.0127)	(0.0144)	(0.0159)	(0.0169)
Middle/high school	–0.0261***	–0.0305**	–0.0263	–0.0228	–0.0140	–0.0169
	(0.00886)	(0.0142)	(0.0173)	(0.0190)	(0.0212)	(0.0228)
Elementary/middle/high school	–0.0601***	–0.0797***	–0.0802**	–0.0810**	–0.0896*	–0.0927*
	(0.0140)	(0.0257)	(0.0312)	(0.0368)	(0.0476)	(0.0503)
Title 1—targeted assistance	0.00947**	0.0176**	0.0117	0.00388	–0.00382	–0.0159
	(0.00429)	(0.00736)	(0.00891)	(0.00964)	(0.0108)	(0.0111)
Title 2—school wide	0.00782***	0.0119**	–0.000352	–0.00420	–0.00720	–0.00892
	(0.00302)	(0.00532)	(0.00735)	(0.00843)	(0.00924)	(0.00996)
Medium size	0.0100***	0.0136**	0.0154**	0.0163**	0.0139*	0.0126
	(0.00341)	(0.00577)	(0.00703)	(0.00777)	(0.00822)	(0.00857)
Student–teacher ratio	–0.00779***	–0.00870***	–0.00843***	–0.00865***	–0.00783***	–0.00685***
	(0.000576)	(0.000879)	(0.00111)	(0.00123)	(0.00141)	(0.00147)

VARIABLES	1-year attrition rate	2-year attrition rate	3-year attrition rate	4-year attrition rate	5-year attrition rate	6-year attrition rate
Teacher population						
Percentage of novice teachers	0.136***	0.218***	0.259***	0.280***	0.301***	0.289***
	(0.0132)	(0.0210)	(0.0248)	(0.0273)	(0.0297)	(0.0321)
Percentage of teachers with masters or higher	–0.0435***	–0.0621***	–0.0723***	–0.0671***	–0.0708***	–0.0686**
	(0.00884)	(0.0153)	(0.0199)	(0.0233)	(0.0256)	(0.0272)
Percentage of non-White teachers	0.0947***	0.140***	0.146***	0.145***	0.144***	0.143***
	(0.0104)	(0.0177)	(0.0225)	(0.0258)	(0.0282)	(0.0295)
Percentage of teachers out-of-state prepared	0.00175	–0.0120	–0.0222	–0.0311	–0.0434	–0.0406
	(0.0138)	(0.0230)	(0.0293)	(0.0339)	(0.0375)	(0.0403)
Percentage of teachers prepared through alternative certification	0.0562	0.205***	0.321***	0.312***	0.230***	0.191***
	(0.0350)	(0.0553)	(0.0589)	(0.0587)	(0.0618)	(0.0605)
Percentage of teachers with conditional certification	0.0937***	0.193***	0.243***	0.303***	0.341***	0.285***
	(0.0306)	(0.0531)	(0.0649)	(0.0621)	(0.0590)	(0.0551)
Student population						
Percentage of students with free and reduced-price meals	–0.0196***	–0.0314***	0.0124	0.0368*	0.0454*	0.0619**
	(0.00604)	(0.0114)	(0.0191)	(0.0221)	(0.0239)	(0.0251)
Percentage of students with disability	–0.0261	–0.0254	–0.0283	–0.0181	0.00939	0.0259
	(0.0186)	(0.0287)	(0.0362)	(0.0396)	(0.0513)	(0.0500)
Percentage of student English learners	–0.0392***	–0.0625***	–0.0812***	–0.0917***	–0.0498*	–0.0459*
	(0.0112)	(0.0172)	(0.0225)	(0.0250)	(0.0262)	(0.0262)
Average student days absent	0.00111***	0.00223***	0.00284***	0.00289***	0.00288***	0.00279***
	(0.000305)	(0.000560)	(0.000690)	(0.000758)	(0.000816)	(0.000814)
Percentage of minoritized students	0.0143*	0.0486***	0.0778***	0.0939***	0.0991***	0.101***
	(0.00816)	(0.0135)	(0.0177)	(0.0208)	(0.0227)	(0.0237)
Percentage of students female	0.0345*	0.0113	0.0169	0.0312	0.0315	0.0409
	(0.0207)	(0.0340)	(0.0459)	(0.0512)	(0.0566)	(0.0595)
Percentage of students proficient or above ELA	0.0607***	0.0919***	0.103***	0.131***	0.126**	0.159**
	(0.0196)	(0.0311)	(0.0365)	(0.0404)	(0.0503)	(0.0640)
Percentage of students proficient or above math	–0.0927***	–0.151***	–0.155***	–0.173***	–0.162***	–0.188***
	(0.0190)	(0.0301)	(0.0350)	(0.0368)	(0.0437)	(0.0550)

Models predict multiyear average attrition rates (chronic attrition measures) from school features. School-year clustered standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

37.0%, 4-year attrition rates of around 45.4%, 5-year attrition rates of around 52.5%, and 6-year attrition rates around 58.1%. The average school experiences 2- to 6-year average attrition rates between 14.6% to 15.4% (with small increases with the addition of each additional year).

These models offer R^2 values between 0.575 and 0.328, indicating these models explain a good deal of variation, although not all, and will serve as a strong set of controls for the models used to test Assumption 3. Furthermore, these analyses taken together with the descriptive data suggest that it is typical for schools to experience up to 45% attrition over three years, and up to 60% attrition over six years. These initial estimates of typicality for each attrition type serve as a guidepost for interpreting the outcomes of the analyses under Assumption 3.

Assumption 1 Implications

Several key patterns have emerged from exploring this assumption. First, by examining multiple descriptives there is some convergence of analyses that suggest a minimum threshold for typicality for each measure: below 17% for 1-year attrition rates, below 17% for 3-year average attrition (chronic attrition), and below 45% for 3-year attrition (cumulative attrition). These rates are both common across the means of multiple subgroups of school types. They are rates experienced by a majority of schools and thus on their face serve as a logical minimum barrier for typicality. Given that I ultimately defined typicality in contrast to atypicality as association with student outcomes, these values serve as a starting point for later analyses.

Second, each type of attrition rate varies somewhat consistently across a set of school, teacher, and student population features. Controlling for these features must be accounted for in models used in later stages of this analysis. Without inclusion of these controls, the analysis may be biased due to the unequal distribution of these features across schools. This also suggests that while Assumption 3 intends to suggest universal benchmarks, future inquiries may also need to address how these benchmarks are relevant across specific subsets of schools.

Assumption 2 Analyses

A2 posits that "over time, schools experience different forms of atypical longitudinal attrition." The purpose of this analysis stage is to explore the extent to which individual schools' patterns of attrition vary over time while also gaining understanding of the mechanical relationship of the measures used for later stages of this analysis. To explore this, I began by examining the patterns of individual schools and the extent to which these patterns suggest, preliminarily, that some subgroups of schools experience different patterns during this period. I began this analysis by generating a series of spaghetti plots of school patterns of 1-year attrition over time. Next, I examined patterns of accumulated attrition over time. Finally, I examined the extent of correlation and overlap between various measures. These analyses suggest that while schools experience considerable variation over time, limiting analyses to a smaller subset of measures is more appropriate.

School-Level Patterns Over Time

Figure 4.12 displays a random sample of 100 schools[12] in a spaghetti plot. Each line represents one school, plotting attrition rates between 2009–2019. This figure shows greater concentration of attrition rates below 20%, with the highest spikes typically only sustained for a single year. However, this plot also includes a few examples of schools that appear to sustain rates above 30% over multiple years and some that tend to remain below that point.

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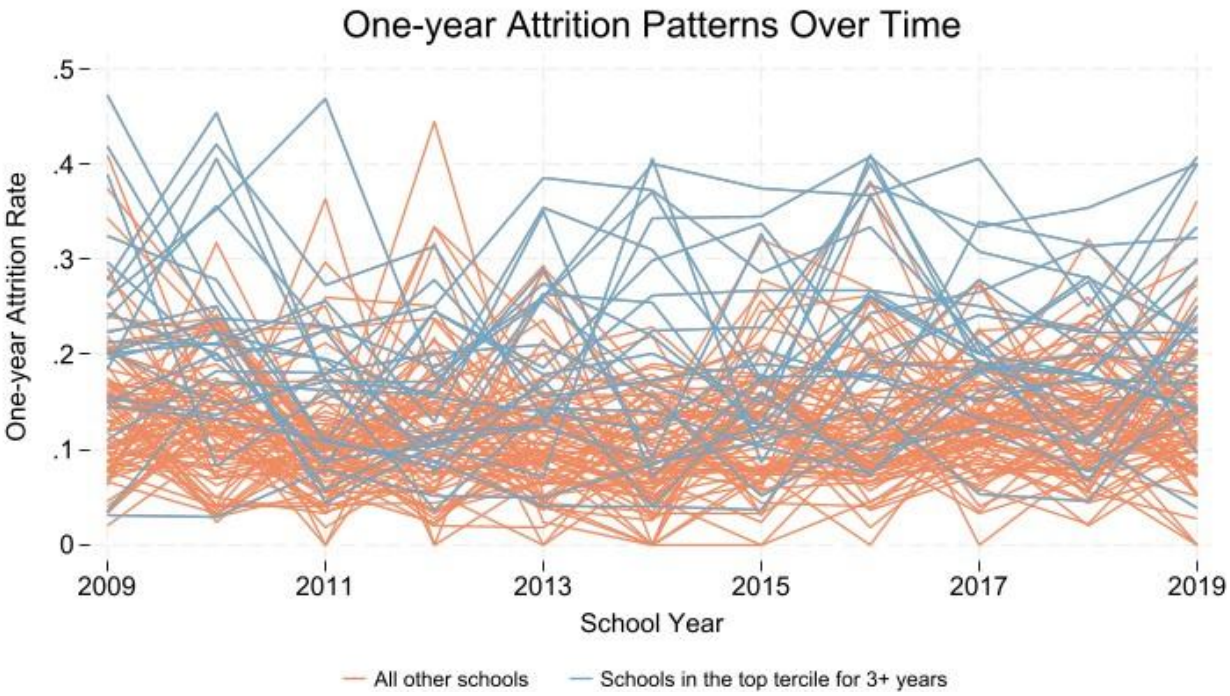
[12] A sample of schools was chosen rather than plotting all schools, as the density of the full plot rendered the visual unreadable.

Figure 4.12

Sample of 100 Schools—1-Year School Level Attrition Patterns Between 2009–2019



Each line represents a single school. Each point on the line represents the school's 1-year attrition rate in the given school year. Blue lines represent schools in the top tercile of 1-year attrition rates for three or more years. Orange lines represent all other schools.

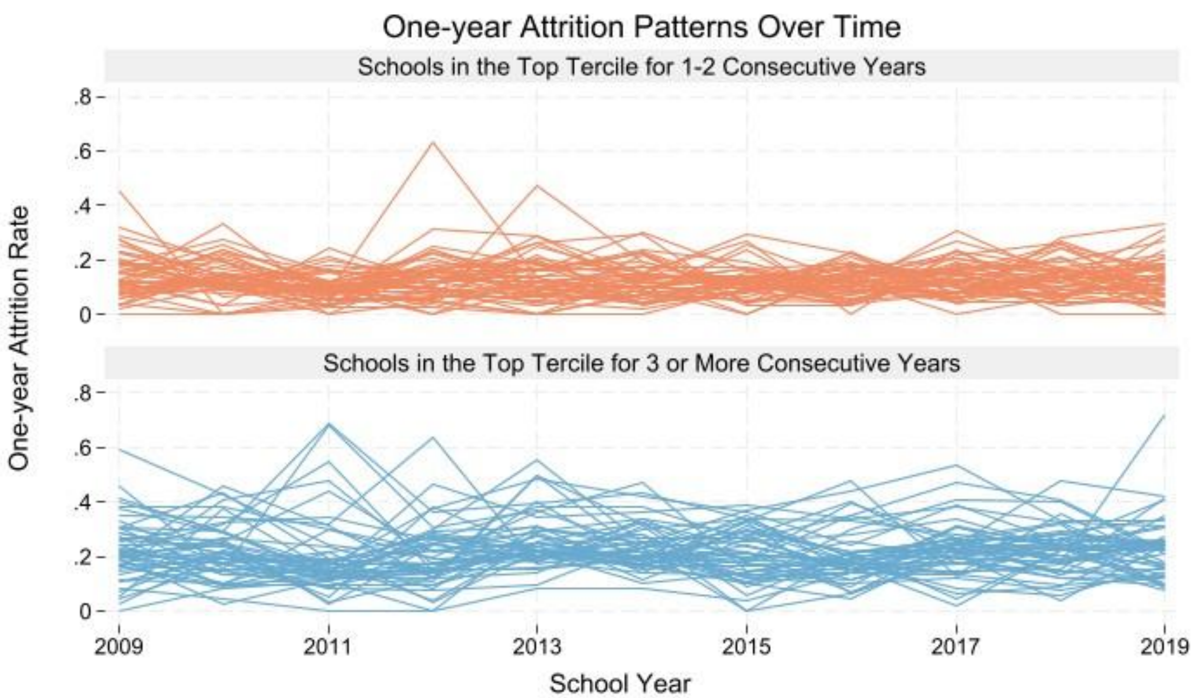
While later stages of this analysis focus on identifying appropriate thresholds for "high" attrition, I used the top tercile (or third) of observations as an indicator of relatively elevated attrition. Most schools (1,107) experience one year where their attrition rate falls into the top tercile (or third) of observations for that year. Conversely, only 107 schools never fall into this category, suggesting it is somewhat common for schools to experience elevated attrition occasionally.

To better assess the patterns of the schools that experience at least one year in the top tercile, I created a split visual year. In Figure 4.13 the bottom panel contains schools that experience three or more consecutive years in the highest tercile of 1-year attrition rates for elevated attrition during this period; only 30.7% of all schools (35.4% of schools with at least one year in the top tercile) experienced a sustained streak of relatively elevated attrition. This visual excludes schools that were never in the top tercile of 1-year attrition rates. The top panel contains schools that experience at least one but not more than two consecutive years in the highest tercile of 1-year attrition rates for that school year (n=715). This means that while 86.70% of schools experienced one year of sustained relative elevated attrition, there is much variation within the period examined.

While these visuals provide some insights into patterns within schools over time, the plots' density makes it difficult to see the true extent of the variation. To address this, I analyzed

Figure 4.13

One-Year School Level Attrition Patterns 2009–2019 by Number of Years Spent in the Top Tercile—Sample of 100 Schools



Each line represents a single school. Each point on the line represents the school's 1-year attrition rate in the given school year. Blue lines represent schools in the top tercile of 1-year attrition rates for three or more years. Orange lines represent all other schools.

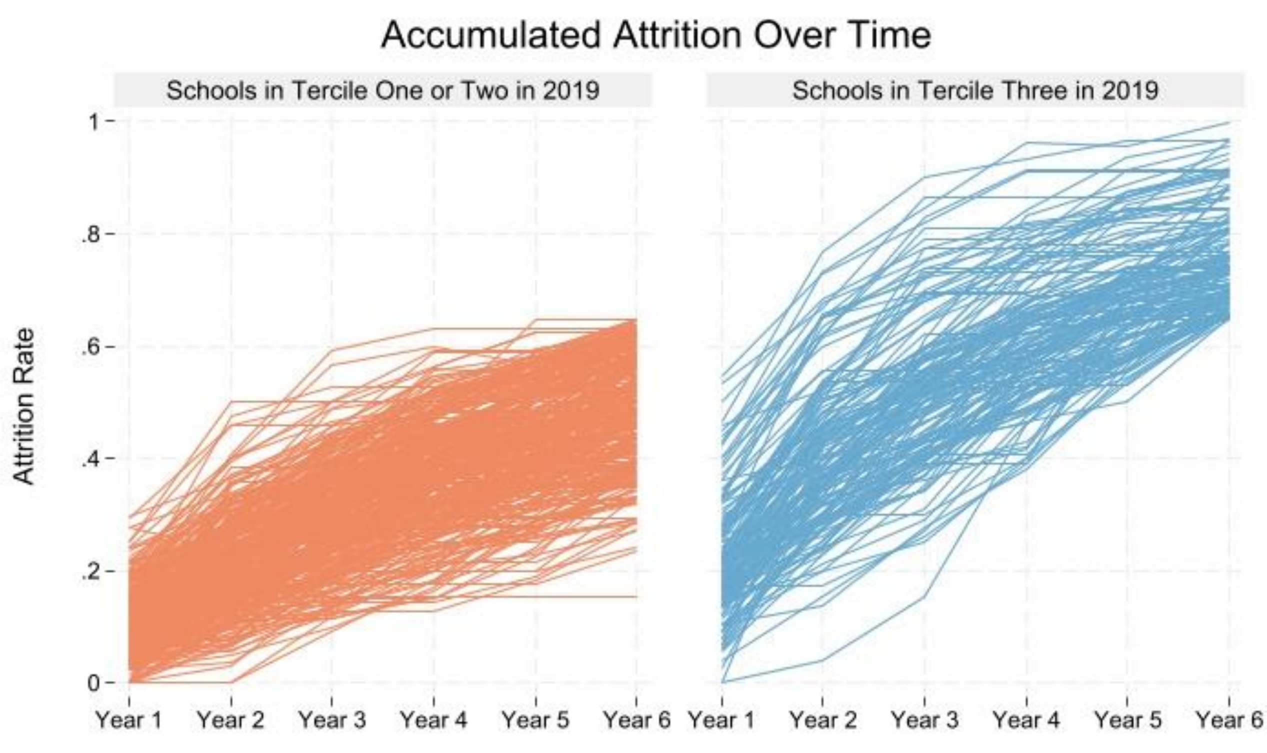
a random sample of the trajectories of 200 schools. In Figure 4.14, blue lines represent schools experiencing three consecutive years of attrition in the top tercile; orange lines represent schools that did not. This figure reinforces the findings from Figure 4.13 that even among schools experiencing multiple years of attrition in the top tercile, those schools do not always sustain those long-term patterns. However, few of these schools spend a sustained amount of time at the lowest end of the spectrum, with only a small number of schools experiencing years with less than 5% attrition. Taken together, analysis of these spaghetti plots of 1-year attrition rates over time strongly indicates that schools experience a variety of year-to-year changes in attrition rates and that a subset of schools may experience multiple years of relatively high attrition or chronic attrition. This suggests that it may be atypical for a school to experience many years of high attrition. In addition to seeing how 1-year attrition rates vary from year-to-year, spaghetti plots offer insight into how schools experience compositional changes over time. I plotted the trajectory of each school's accumulated attrition from Year 1 in 2014 to Year 6 in 2019 to analyze how the percentage of departing staff grows over time. Figure 4.14 displays the trajectories of schools that end in the highest tercile of 6-year attrition rates on the right and all other schools on the left. This figure shows that schools in the highest tercile by Year 6 (2019) start in Year 1 with attrition rates across the full range observed in that year (between 0% to just over 50% in 2014). While some schools that end Year 6 in the top tercile also start on the top end of the range, the presence of schools in this group that experience the lowest possible rates of attrition in Year 1 suggests that a school's trajectory in Year 6 is not fully predictable from a single year of attrition. There is significant overlap between the lines from Year 1 (2014) through Year 3 (2016), after which the overlap is minimal. Furthermore, this figure shows a greater variation in 6-year attrition rates than in initial 1-year attrition rates, suggesting that schools experience differing patterns on this dimension over time as well. This finding further suggests preliminary evidence that a subset of schools repeatedly experience high attrition rates and some subset schools accumulate high rates of turnover over time, offering preliminary evidence of the existence of schools experiencing both chronic and cumulative attrition.

Analysis of Distinctiveness

While these initial explorations provide evidence that some schools experience both chronic and cumulative attrition, additional analyses are necessary to assess the distinctness of

Figure 4.14

Accumulated School-Level Attrition 2014–2019 by Tercile Membership in 2019



Each line represents a single school. Each point on the line represents accumulated attrition in the given school year (i.e., 1-year attrition in Year 1, 2-year attrition in Year 2). Blue lines represent schools in the top tercile of attrition rates by year six. Orange lines represent all other schools.

each construct. One way to interrogate this question is to assess the extent of the correlation and overlap between the measures to determine the extent to which schools experiencing high rates of multiyear attrition are also experiencing high rates of multiyear average attrition rates.

Figure 4.7 (discussed in greater detail in the previous section) demonstrates that each of the 2- to 6-year average attrition rates has sufficient variation to be appropriate for multiple regression. Still, these distributions do raise some concerns. In particular, the similarities of the 4- to 6-year average attrition rates emphasize that averaging across multiple years may produce measures with a high level of overlap and thus may not be sufficiently distinct to justify their own analyses.

To examine this more closely, I generated correlations between each multiyear average rate. The results in Table 4.4 indicate a high level of correlation that grows with each additional year. Some correlation is expected given that these measures rely on the same underlying data.

Table 4.4

Correlation Coefficients Between Multiyear Average Attrition Rates (Chronic Attrition Measures)

	1-yr attrition	2-yr avg attrition	3-yr avg attrition	4-yr avg attrition	5-yr avg attrition	6-yr avg attrition
1-yr attrition	1.00					
2-yr avg attrition	0.84	1.00				
3-yr avg attrition	0.77	0.92	1.00			
4-yr avg attrition	0.73	0.88	0.95	1.00		
5-yr avg attrition	0.70	0.85	0.92	0.97	1.00	
6-yr avg attrition	0.68	0.83	0.90	0.95	0.98	1.00

However, the 4-, 5-, and 6-year average attrition rates are over 95% correlated with each other; with this high level of correlation, these figures are likely so similar that it would be almost impossible for them to generate meaningfully distinct patterns.

The distribution of multiyear rates is less consistent across different durations. Each

Table 4.5

Correlation Coefficients Between Multiyear Attrition Rates (Cumulative Attrition Measures)

	1-yr attrition	2-yr attrition	3-yr attrition	4-yr attrition	5-yr attrition	6-yr attrition
1-yr attrition	1.00					
2-yr attrition	0.82	1.00				
3-yr attrition	0.73	0.91	1.00			
4-yr attrition	0.69	0.85	0.94	1.00		
5-yr attrition	0.65	0.81	0.88	0.95	1.00	
6-y attrition	0.63	0.78	0.86	0.91	0.96	1.00

additional year produces a distribution with a greater range and flatter distribution as shown in Figure 4.8. Table 4.5 displays the correlation coefficients for the multiyear rates. These measures have weaker correlations than the multiyear average rates but still see high levels of correlation between 4-, 5-, and 6-year attrition rates. This additional comparison suggests a high level of correlation amongst the longest durations for both sets of attrition rates. It is unlikely that measures with such extremely high overlap are meaningfully distinct. Thus, while using these measures to examine differences across a 4-year period may be possible, using average rates for durations beyond four years would not be wise.

In addition to examining the level of overlap between each group of interim measures, it is also important to examine the level of correlation between the corresponding multiyear average and the multiyear rates. This analysis aids in determining the extent to which schools might be experiencing each of these phenomena distinctly or concurrently. As shown in Table 4.6, the variation between the two measures grows with each additional year of data. These metrics do not have less than 95% correlation until Year 3 and above. However, all paired comparisons have a correlation above 90%, indicating a high level of overlap across these measures.

Table 4.6

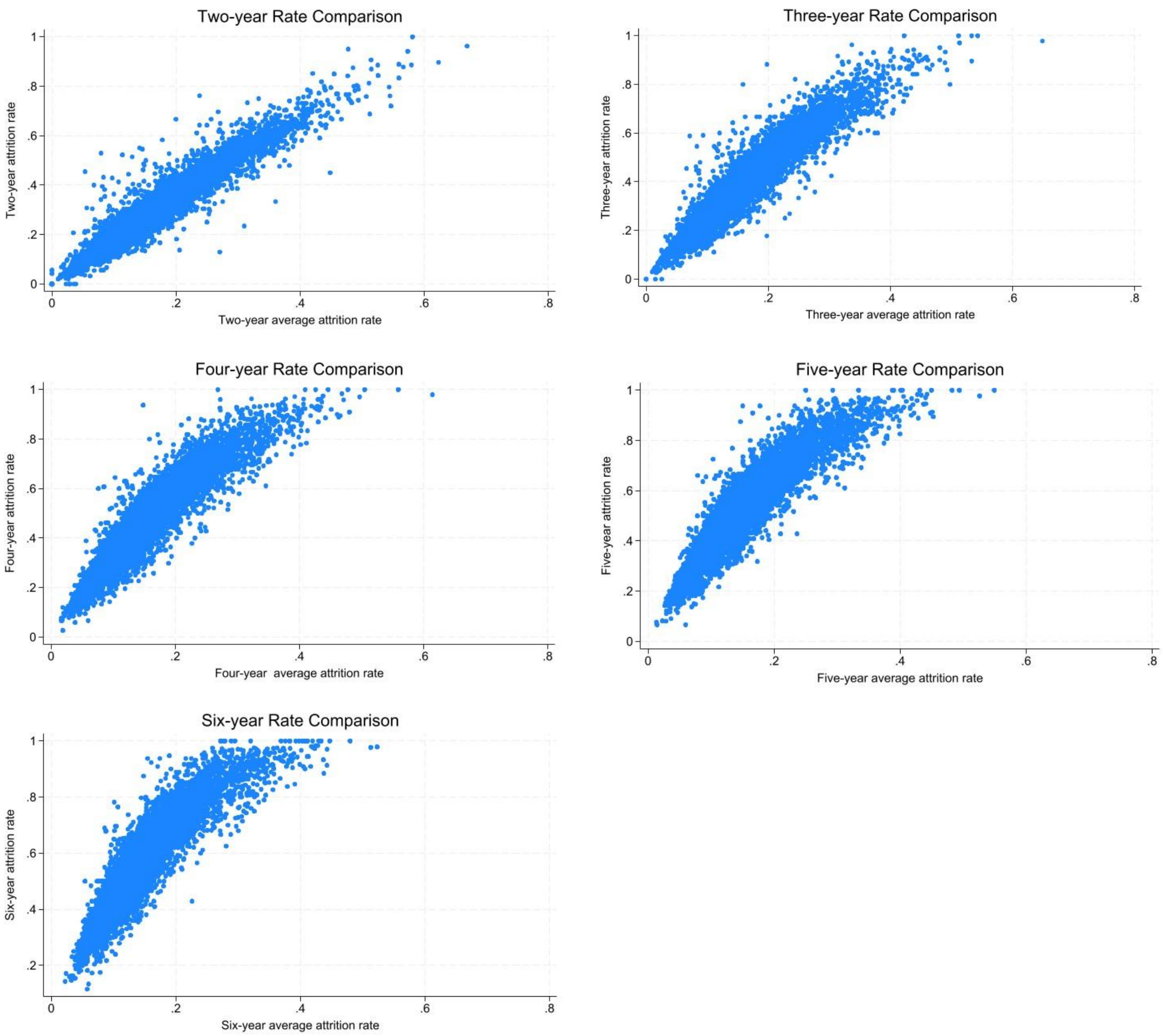
Correlation Coefficients Between Duration Matched Pairs of Multiyear Attrition Rates and Multiyear Average Attrition Rates

		Cumulative Attrition Measures				
		2-yr attrition	3-yr attrition	4-yr attrition	5-yr attrition	6-yr attrition
Chronic Attrition Measures	2-yr avg attrition	.98				
	3-yr avg attrition		.97			
	4-yr avg attrition			.96		
	5-yr avg attrition				.94	
	6-yr avg attrition					.93

The scatterplots (Figure 4.15) show greater variation at the upper end of each distribution, particularly amongst the fifth year and sixth year as more schools approach the cap of 100% turnover. However, the combined analyses suggest that, despite chronic and cumulative attrition being theorized as distinct constructs, schools with high turnover across multiple years typically experience consistently high annual attrition rates rather than the accumulation of low 1-year rates. Since instances of these constructs occurring separately are rare, this dataset is not well suited to examine them as independent phenomena.

Figure 4.15

Scatter Plots of Pooled Paired Duration Attrition Rates



Scatterplots depict the relationship between school-year observations duration, matched multiyear attrition rate (cumulative attrition measures), and multiyear average attrition rate (chronic attrition measures).

For this project, I focused on chronic rather than cumulative attrition, as the 2- to 6- year attrition measures track the attrition of a single cohort of teachers without accounting for replacement staff who leave within the same period. Given the focus of this study on developing policy-relevant metrics for these constructs, year-over-year average attrition provides a more practical and consistent measure than cumulative turnover from an arbitrary starting point. Thus, subsequent analyses conducted under A3 focus on examining multiyear average attrition rates to develop a metric for chronic attrition.

Additionally, because the 5-year and 6-year average attrition rates are mechanically so similar to the 4-year average attrition rate, they are excluded from further analysis. Limiting analyses to a 4-year time period allows access to two additional years of outcome data for the inferential analyses, enabling the inclusion of sixth graders attending middle schools between 2016–2019. Descriptive statistics for this sample are provided in Appendix B.

Assumption 2 Conclusions

This section examined Assumption 2, "over time, schools experience different forms of longitudinal attrition," and focused on building understanding of the patterns experienced within schools over time. The evidence does not fully support this assumption; instead, while analyses indicate that schools may experience differing patterns of longitudinal attrition, correlational analyses reveal that they generally do not experience different unique forms of longitudinal attrition over time. Examination of individual school patterns over time via spaghetti plots suggests substantial variation in longitudinal patterns; however, examination of correlations and scatterplots suggests a high level of overlap between the different measures. Thus, while this project intended to examine three constructs, I instead focused on the remainder of the analyses on two constructs: episodic and chronic attrition. Additionally, due to reduced variation for 5- and 6-year average measures, I further limited subsequent analyses to 1- to 4-year durations to ensure that each measure is not too mechanically similar. I applied both these refinements in analyses for A3.

Chapter 5: Assumption 3—Findings and Implications

Introduction

This chapter summarizes the findings of an inquiry into the final assumption of this dissertation and the primary assumption that will be used to inform the development of policy-relevant metrics of longitudinal teacher attrition. This section advances a predictive validity argument and focuses on inferential analyses that model the relationship between varying durations of teacher staffing instability and student achievement in ELA and math. A3 states, "Atypical forms of teacher attrition are harmful to students, and more disruptive forms of teacher attrition will be associated with more severe negative student outcomes." Thus, this analysis is intended to identify thresholds for atypicality vis-à-vis student outcomes. I began by conducting a model fitting to explore nonlinearities between teacher attrition and student achievement. Next, I compared the average marginal effects of each preferred model to identify the extent to which differing durations and attrition rate intensities predict harmful student outcomes.

Functional Form Examination

To examine nonlinearities within the relationship between teacher attrition and student achievement, I compared standard linear models for each attrition rate with models that included three other exponential terms. As shown in Table 5.1, Model 1 included the initial linear model described in Chapter 3, Model 2 included a quadratic term, and Model 2 included a cubed term.[13] The results of this analysis suggest that the functional form of the relationship between school-level attrition and student achievement is nonlinear in nature.

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[13] Regression coefficients for each model are available in Appendix D.
I also examined models that included a natural log transformation of the attrition predictions, but these models did not provide a strong fit for the data.

Table 5.1

Model Functional Form Comparison

	Predicting math achievement			Predicting ELA achievement		
	(1)	(2)	(3)	(1)	(2)	(3)
	Linear	Quadratic term	Cubic term	Linear	Quadratic term	Cubic term
1-year attrition rate						
AIC	269644.42	269636.31	269637.5	296300.1	296299.2	296300.2
ΔAIC	8.1	0.0	1.2	0.9	0.0	1.0
2-year average attrition rate						
AIC	268306.87	268293.65	268295.5	294784.1	294783	294784.8
ΔAIC	13.2	0.0	1.9	1.1	0.0	1.8
3-year average attrition rate						
AIC	267301.43	267292.91	267291.9	293648.7	293644.5	293643.4
ΔAIC	9.5	1.0	0	5.4	1.1	0
4-year average attrition rate						
AIC	266523.5	266517.58	266514.9	292775	292773.8	292769.4
ΔAIC	8.6	2.7	0	5.6	4.4	0

Following Burnham and Anderson (2004), comparison of AIC across models indicates that for 1-year attrition and 2-year average attrition, Model 2 (quadratic term) is the strongest fit. For the 3-year average attrition and 4-year average attrition, there is a slight preference for Model 3 (cubic term). However, there is moderate evidence of strong fit for Model 2 as well.

I further examined the predicted marginal effects for both Model 2 and Model 3 to gain a better sense of how the functional form changes the shape of the distribution. Visual examination of these patterns suggests two key things. As shown in Figure 5.1 and Figure 5.2 in the area of the distribution where observations are concentrated (within one standard deviation of the mean), these models produce almost identical estimates. It is only in the tail of each distribution where these estimates diverge.

Figure 5.1

Functional Form Comparison: Predicting Math Achievement From 3-Year Average School-Level Attrition

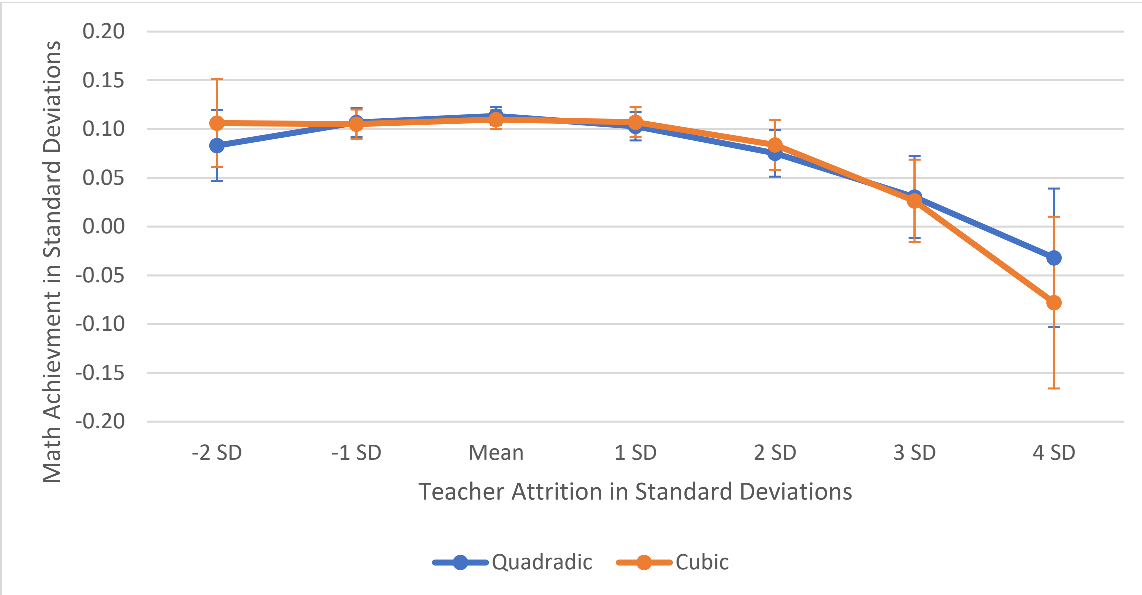
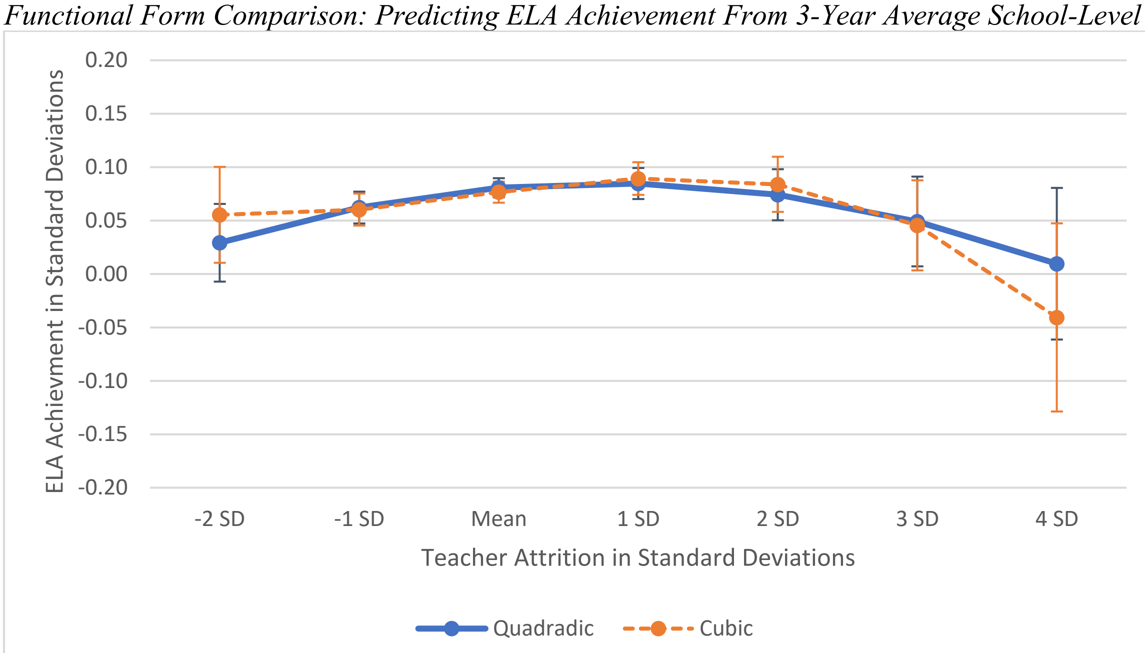


Figure 5.2

Functional Form Comparison: Predicting ELA Achievement From 3-Year Average School-Level Attrition



Figures 5.1 and 5.2 average marginal effects of teacher attrition on student math or ELA achievement with 95% confidence intervals. Blue lines display predictions from models that include a quadratic attrition term. Orange lines display predictions from models that include a cubic attrition term. Dotted lines indicate models that are marginally significant.

Note that across both outcomes, compared to Model 2, Model 3 predicts higher estimates starting at two standard deviations below the mean and lower estimates starting at two standard deviations above the mean. While Model 2 would predict a reduction in student achievement, selecting Model 2 rather than Model 3 would result in an underestimate of the magnitude of the relationship between teacher attrition and student outcomes for attrition rates over 3 standard deviations above the mean. However, selecting Model 2 rather than Model 3 would change the direction of the relationship between teacher attrition and student outcomes for attrition rates less than 1 standard deviation below the mean. For that reason, I interpreted this portion of the distribution with great caution.

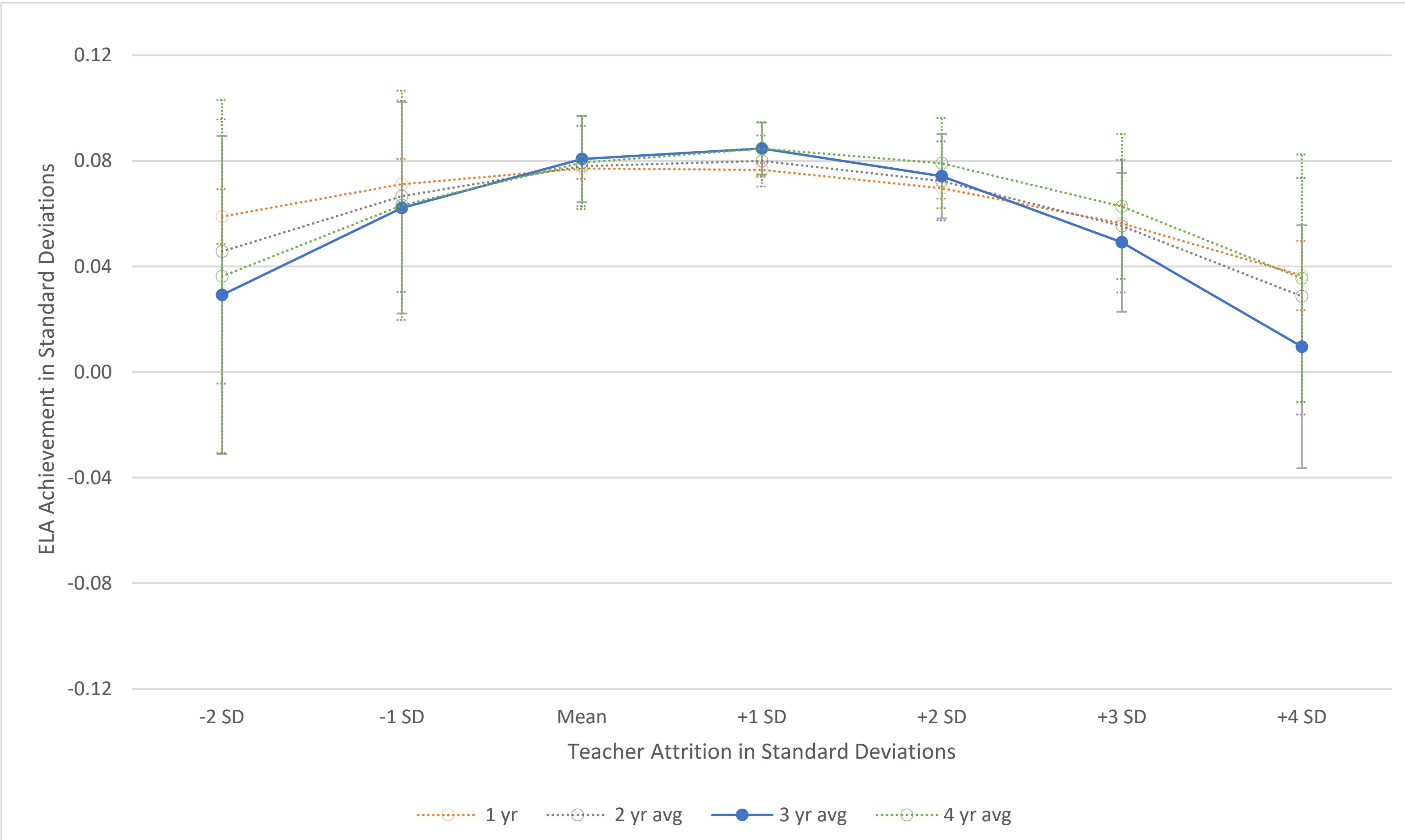
Ultimately, given a preference for a simpler model and consistency across attrition measures, I chose Model 2 as the preferred model, concluding that the quadratic model offers a stronger fit across measures and outcomes. As a result, it serves as the primary functional form in subsequent analyses. This analysis provides strong evidence for the inclusion of nonlinear terms when modeling longitudinal attrition measures and allows for the further interrogation of potential policy-relevant thresholds for the measures. Continuing to probe the preferred models, the next section explores how the duration and intensity of elevated attrition patterns shape student outcomes over time.

Duration and Divergence of Patterns

Having established that the quadratic model is appropriate for the data, this section examines how the duration and intensity of multiyear average attrition rates are associated with student outcomes over time. This analysis shows that across multiple models, attending a school for a single year with a pattern extreme high rates of teacher attrition over multiple years is associated with lower achievement in both ELA and math compared to attending a school with

Figure 5.3

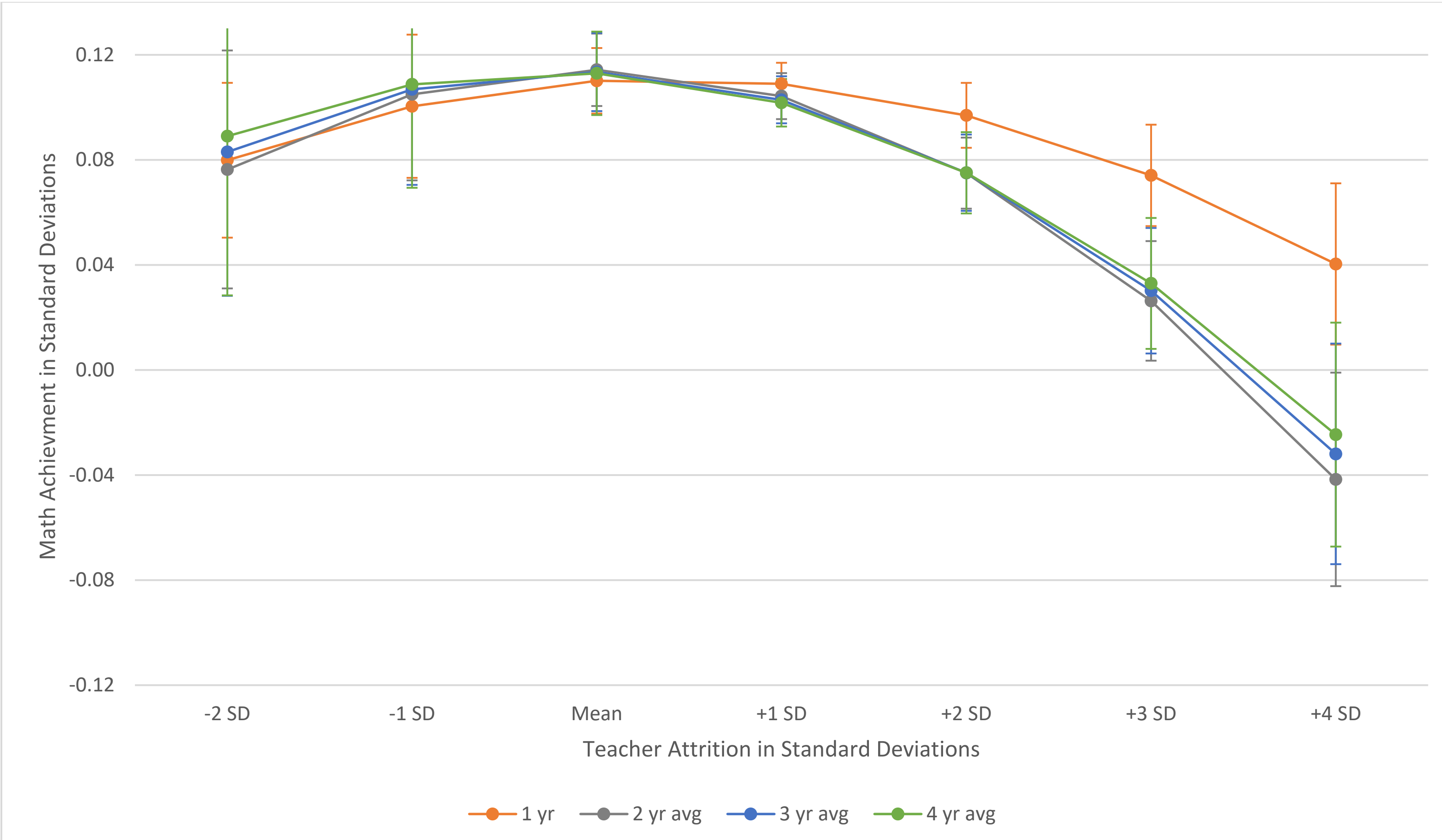
Average Marginal Effects of Teacher Attrition Measures on ELA Achievement (With 95% Confidence Intervals)



Each line charts results from different models predicting average marginal effects of 1- 2-, 3- and 4-year average teacher attrition on ELA achievement with 95% confidence intervals. Dotted lines indicate models that are marginally significant.

Figure 5.4

Average Marginal Effects of Teacher Attrition Measures on Math Achievement (With 95% Confidence Intervals)



Each line charts results from different models predicting average marginal effects of 1- 2-, 3- and 4-year average teacher attrition on math achievement with 95% confidence intervals. Dotted lines indicate models that are marginally significant.

an average attrition rate.

As shown in Figure 5.3, the inclusion of quadratic terms in the model predicts an inverted U-shaped relationship between school-level attrition and ELA achievement (regression coefficients included in Appendix E). Specifically, this model predicts that moderate levels of achievement are associated with the highest student outcomes, while both very low and especially very high levels of attrition predict lower ELA outcomes. This pattern is consistent with organizational theorists and education scholars who suggest that some degree of turnover can be healthy, promoting renewal and adaptability within the organization (Dalton & Todor, 1979; Wallace & Gaylor, 2012), and can serve as a driver for improved student outcomes (Hanushek, 2009). However, it is also worth noting that the confidence intervals for the achievement dip at the lower end of the attrition distribution overlap with those at the peak. This suggests that the decline in performance at very low attrition levels may not be statistically distinguishable from the peak achievement levels, indicating greater uncertainty in this portion of the prediction. This, coupled with the cubic functional form predicting higher student achievement in math and ELA at this point in the distribution, I refrained from too much speculation based on this portion of the estimates.

Among the different measure durations examined, the 3-year average attrition measure (solid blue line) demonstrates the clearest and most stable pattern, showing a slight increase in ELA achievement that peaks around 1 standard deviation above the mean, followed by a consistent decline beyond that point.

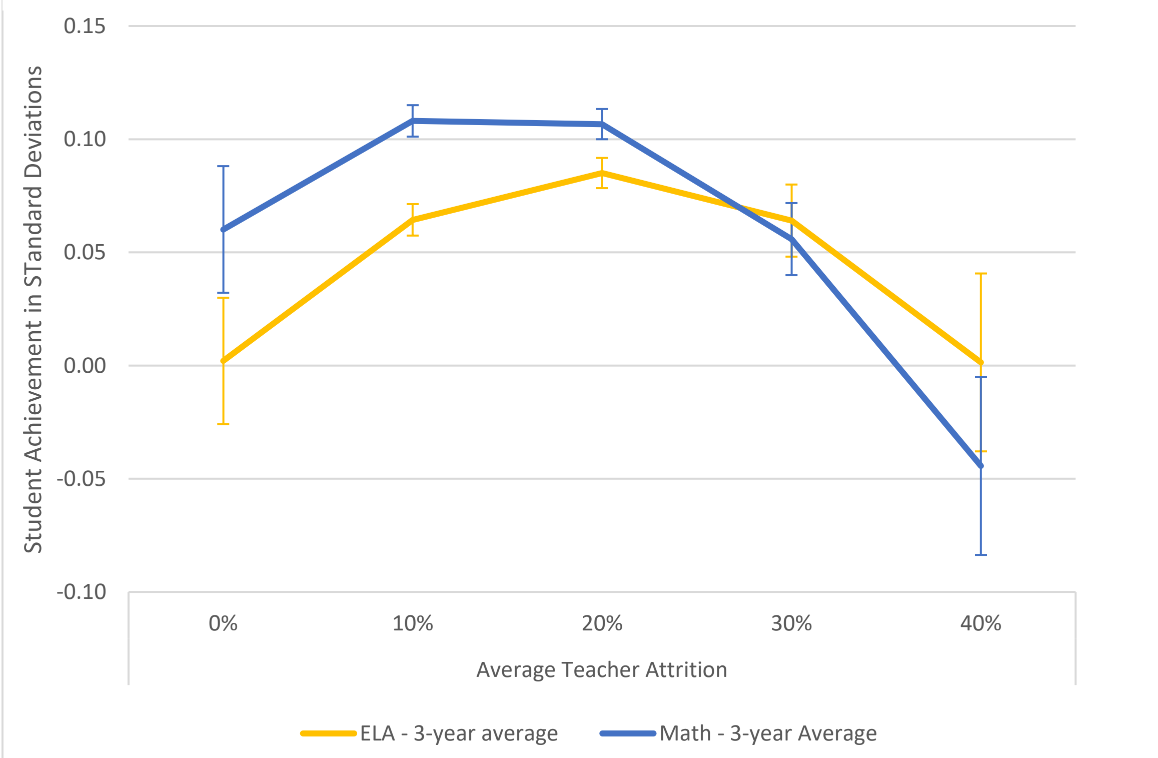
Similar patterns emerge amongst the models predicting math achievement, though with some key differences. All four models again exhibit an inverted U-shaped pattern; however, in this case, the math achievement peaks earlier around the mean to 1 standard deviation above the mean. After the +1 SD mark, math achievement declines at a more rapid rate than predicted by the ELA models, especially for the 3- and 4-year attrition rates. This sharper drop suggests that excessive and sustained attrition may be even more disruptive in math.

Among the four attrition measures examined, only 3-year average attrition rates show statistically significant associations with both ELA and math achievement, which suggests that the 3-year mark may serve as a logical choice as a duration threshold for chronic attrition.

Despite overall consistency in the findings across measures, the predicted marginal effects show a high degree of overlap in confidence intervals across the 2-, 3-, and 4-year average attrition models, with moderate overlap also observed with the 1-year average attrition model, for the math outcome and similar overlap across all four measures for the ELA

Figure 5.5

Average Marginal Effects of 3-year Average Attrition on Student ELA and Math Achievement (with 95% Confidence Intervals)



outcome.[14] This overlap suggests that there is not sufficient evidence to establish the other rates as statistically distinguishable. These findings do not support the need for a separate measure of episodic attrition.

Intensity of Attrition and Student Outcomes.

The second dimension of the analysis examines the intensity of attrition and its relationship to student achievement. Across both outcomes, 3-year teacher attrition is associated with negative student outcomes at the extreme end of the attrition distribution. To identify more specific inflection points, additional examination of both 3-year average attrition measures is warranted.

While the use of relative thresholds (e.g., standard deviations above the mean) is effective for identifying patterns, it may lack practical utility for policymakers. To offer more actionable guidance, it is necessary to re-examine the models using absolute thresholds by removing the scaling on the x-axis.

As shown in Figure 5.5, the inflection point—the level at which achievement begins to decline—differs slightly by subject. For ELA this pattern becomes most pronounced around 30%, while for math this occurs around 20%. Moreover, the math achievement pattern demonstrates both a higher peak at the center of the distribution and a steeper drop in achievement between the peak and the high end of the distribution, suggesting that math outcomes are more sensitive to excessive attrition. In short, both subjects reflect the same overall pattern, but math achievement appears more responsive to high attrition rates. Nonetheless, the

[14] Comparison of coefficients for alternative models with school-level clustered standard errors was conducted using seemingly unrelated estimates (SUEST) tests (Mize et al., 2019). The results of these tests confirm that these models are not statistically different.

30% threshold emerges as a critical point beyond which student achievement tends to decline across both subjects.

To further validate the 30% threshold as a policy benchmark, I compare schools that fall into distinct attrition categories based on absolute rates rather than relative thresholds. This involves grouping school-year observations into distinct categories. In this case, I create groups based on 10–5 percentage point intervals roughly aligned with standard deviation thresholds. While this grouping strategy removes nuance within each category, it allows an accessible way to make direct comparisons between different points within the distribution. Furthermore, in addition to these comparisons, this approach also allows for a renewed examination of functional form by revealing whether outcomes vary systematically across distinct ranges of the predictor.

Table 5.2

Student Achievement Outcomes by Magnitude of Chronic Attrition (3-Year Average Attrition)

VARIABLES	(1) Math	(2) ELA
3-year average attrition <=10%	0.0617**	0.0340
	(0.0313)	(0.0343)
10% to 15%	0.0751**	0.0453
	(0.0295)	(0.0324)
15% to 20%	0.0852***	0.0568*
	(0.0281)	(0.0309)
20% to 30%	0.0627**	0.0641**
	(0.0272)	(0.0298)
Observations	204,360	204,501
Number of groups	903	902

Models predict student math or ELA achievement from school-level attrition rates. Models include controls for a set of student characteristics, including prior-year achievement, a set of school characteristics and features, a set of school-level teacher characteristics, and district- and academic-year indicators. Models include school-year random intercepts. Standard errors in parentheses. The comparison group is schools experiencing a 3-year average attrition greater than 30%.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.2 shows that attending a school with a 3-year attrition rate between 15% and 20% (slightly above the mean)—as opposed to a school with a 3-year attrition rate at or above 30%, is associated with a 0.0852 standard deviation increase in math achievement and a marginally significant 0.0568 standard deviation increase in ELA achievement. These estimates are on par with those observed by other scholars (Ronfeldt et al., 2013; Sorensen & Ladd, 2020), suggesting that even school-level turnover that is not localized to particular content areas or grade levels can be associated with harm to students. These models also predict higher math achievement across all groups compared to schools experiencing 3-year average attrition above 30%. This blunter model confirms that although crude, the 30% benchmarks for episodic and chronic attrition appear to serve as critical thresholds, As hypothesized, the groups formed from these benchmarks are associated with differences in student outcomes, suggesting that schools experiencing 3-year attrition rates above 30% would be an appropriate threshold for chronic attrition.

Additionally, as shown in Figures 5.6 and 5.7, this categorical model confirms the selection of the quadratic form by demonstrating a clear, nonlinear pattern in student outcomes across discrete attrition bands: achievement increases at moderate levels of attrition and declines at higher levels, mirroring the inverted U-shape identified in the quadratic models. This shape reinforces the idea that the relationship is not linear and follows a curvilinear trajectory, further supporting the use of the quadratic functional form in earlier models.

Further validation using grouped attrition bands confirms that students in schools with attrition rates between 15%–20% outperform those in schools with attrition at or above 30%, especially in math. Ultimately, the analysis supports the interpretive argument that

Figure 5.6

Average Marginal Effects of Categorical Teacher Attrition Measures on Math Achievement (With 95% Confidence Intervals)

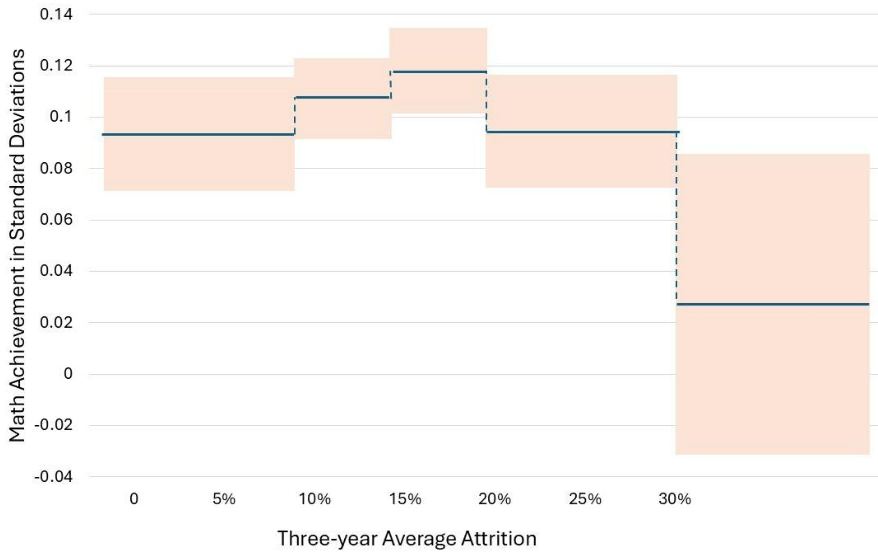
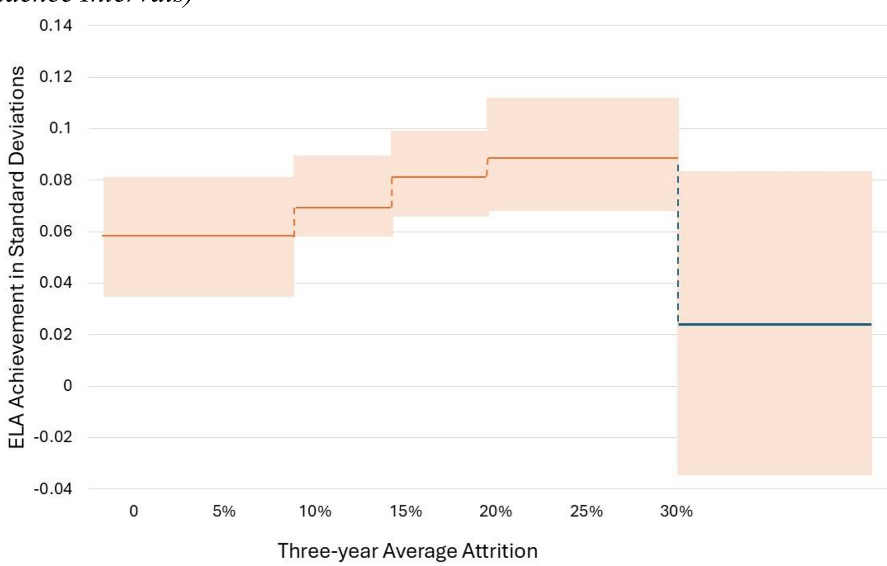


Figure 5.7

Average Marginal Effects of Categorical Teacher Attrition Measures on ELA Achievement (With 95% Confidence Intervals)



Figures depict predicted ELA or math achievement for a model that includes five categories of 3-year teacher attrition categories (0%–10%, 10%–15%, 15%–20%, 20%–30%, >30%). Blue lines represent predictions that are statistically significant from the >30% category; orange lines are not statistically significant compared to that category. Orange shaded areas denote 95% confidence intervals for these estimates.

chronic, sustained attrition above 30% is atypical and harmful and suggests that this threshold may serve as a policy-relevant benchmark for identifying schools at risk.

Sensitivity Analyses.

To ensure the robustness of the primary findings, I conducted additional supplemental analyses to ensure that the relationships observed in the primary analyses are not overly dependent on a singular analytic approach. I provided two key sensitivity analyses to serve as a check on the stability and validity of the estimates. First, I reviewed the findings of the model-building process in greater detail which reveals that the inclusion of student-level covariates, particularly prior achievement, significantly improved model fit and explained a substantial portion of the between-school-year variance in both math and ELA outcomes. Second, I examined the results of a school fixed-effect model predicting outcomes from 2-year average attrition using non-overlapping time periods. While this model strengthens internal validity by accounting for time-invariant school characteristics and reducing the risk of reverse causality, it does not eliminate all sources of bias, and with the available data, could only be implemented on one possible measure. While the goal of this project is not to make a causal claim, this additional analysis enhances the confidence with which these measures can be used to inform policy and practice.

I employed a stepwise model-building process, not primarily to optimize model fit, but to assess the extent to which the coefficient of interest (the association between school-level teacher attrition and student achievement) was sensitive to the inclusion of additional covariates. As such, I began with a simple specification that included only the average attrition rate (Model 2) and sequentially added blocks of controls to evaluate how the estimated relationship changed. Model 1 is a null model that includes only a random intercept to estimate the baseline variation

Table 5.3

Model Building: Preferred Quadratic Models

	Predicting math achievement					
VARIABLES	(1) Null	(2) +Attrition rate	(3) +Student controls	(4) +School controls	(5) +Teacher controls	(6) Full
Average attrition rate (x)		–5.056***	–0.953***	0.304	0.228	0.726**
		(0.803)	(0.314)	(0.297)	(0.302)	(0.301)
Average attrition rate squared (x^2)		–0.335	–.466	–2.007***	–1.557**	–2.469***
		(2.111)	(0.831)	(0.766)	(0.775)	(0.760)
Constant	0.0170	0.113***	0.279***	0.119***	0.117***	0.118**
	(0.0166)	(0.00566)	(0.0273)	(0.0275)	(0.0285)	(0.0459)
Likelihood ratio (LR) chi squared test		538***	258377***	366***	20***	145***
Intercept variance	0.251	0.135	0.019	0.012	0.012	0.010
	(0.012)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
Residual variance	0.761	0.761	0.214	0.214	0.214	0.214
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
	Predicting ELA achievement					
Average attrition rate (x)		–3.251***	0.0336	0.359	0.377	0.832**
		(0.755)	(0.363)	(0.323)	(0.328)	(0.330)
Average attrition rate squared (x^2)		–3.206	–2.058**	–1.317	–1.269	–2.083**
		(1.988)	(0.959)	(0.832)	(0.840)	(0.833)
Constant	–0.00330	–0.00805	0.0462	–0.0289	–0.0292	–0.0866*
	(0.0150)	(0.00614)	(0.0317)	(0.0299)	(0.0309)	(0.0505)
Likelihood ratio (LR) chi^2 test		469 ***	244765 ***	484***	21***	124***
Intercept variance	0.204	0.118	0.026	0.015	0.014	0.012
	(0.010)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Residual variance	0.810	0.811	0.243	0.243	0.243	0.243
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)

Models predict student math or ELA achievement from school-level attrition rates. Model 1 is the null model with no predictors. Model 2 adds the school-level attrition rates. Model 3 adds a set of student characteristics and prior-year achievement. Model 4 adds a set of school characteristics and features. Model 5 adds additional school-level teacher characteristics. Model 6 presents the full conditional model with the inclusion of district- and academic-year indicators. All models include school-year random intercepts. Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

in math and ELA achievement across school-year observations. Model 2 introduces the attrition terms and serves as the primary model for evaluating coefficient stability. Models 3 through 6 then add covariates in blocks: student-level controls (Model 3), school-level characteristics (Model 4), teacher characteristics (Model 5), and finally district and year indicators (Model 6).

As shown in Table 5.3, the inclusion of student-level covariates led to the largest reduction in the size of the attrition coefficient, validating the importance of the inclusion of these characteristics. Inclusion of student characteristics also dramatically reduced the intercept variance between Model 2 to Model 3 from 13.5% to 1.9% in math and from 11.8% to 2.6 % in ELA, demonstrating that much of the between-school variance is driven by student-level variables. Inclusion of the student characteristics reduced the magnitude of the attrition coefficients considerably, resulting in a wider, flatter shape to the form. Despite this reduction in magnitude, attrition still remains a statistically significant predictor of math and ELA achievement.

The inclusion of school and teacher covariates further reduced between-school-year variance, suggesting they explain additional context-specific differences. However, the key purpose of this modeling strategy was not to maximize fit, but to assess whether and how the estimated effect of attrition shifts as plausible confounders are accounted for, particularly when school controls are added, as these likely capture structural factors tied to both staffing and performance.

To further test the robustness of these findings, I also estimated a school fixed effects model, which leverages within-school variation over time to control for unobserved, time-invariant characteristics. Because school fixed effects exploit within-school variation over time, and because this analysis also relies on school-level variation in attrition over time, it is preferable to run this analysis using non-overlapping time periods. Given the limits to the years of data described earlier, this constraint restricts the analysis to the 2-year average attrition measure. While this is not the primary measure of this analysis, it serves as a valuable confirmatory sensitivity check on the robustness of the findings. Results from this specification are consistent with the main findings, lending additional support to the observed association between longitudinal teacher attrition and student achievement.

I construct three non-overlapping 2-year time periods to calculate each school's 2-year average attrition rates in 2015, 2017, and 2019. The results of these models are presented in Table 5.4 alongside the results for the preferred models using the same sample. Consistent with the preferred models presented previously, the school fixed effects model is statistically significant for the math achievement outcome but not for the ELA achievement

Table 5.4

Model Comparison: 2-Year Average School-Level Attrition Predicting Student Achievement

	School fixed effects		School-year random effects	
	(1)	(2)	(3)	(4)
VARIABLES	Math	ELA	Math	ELA
2-year average attrition rate	0.580*	–0.0171	0.364	0.180
(x)	(0.312)	(0.329)	(0.299)	(0.313)
2-year average attrition rate	–1.866**	–0.168	–1.409*	–0.389
(x^2)	(0.807)	(0.835)	(0.736)	(0.772)
School, student, & teacher controls	X	X	X	X
School-year random effect			X	X
School fixed effects	X	X		

Note: Models 1 and 2 predict math and ELA achievement from teacher attrition and include school fixed effects. Models 3 and 4 predict math and ELA achievement from teacher attrition and include school-year random intercepts. All models include school, student, and teacher controls, and district- and academic-year indicators. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

outcome.[15] Although the magnitude of the coefficient for the math outcome as compared to the original models is diminished slightly, they are larger than those generated by the multilevel model using the reduced sample, and across all three the direction and magnitude of the coefficients remain consistent.

These findings reinforce the robustness of the observed relationship between teacher attrition and math achievement, even when applying a more robust modeling approach. The statistical significance and consistent direction of the coefficients across models suggest that the negative effects of high attrition on math outcomes are not an artifact of model choice or sample composition. In contrast, the inconsistent findings for ELA achievement provide additional evidence that the relationship between attrition and this outcome may be less straightforward or that the relationship may be more context-dependent or mediated by other factors not fully captured in the model.

A3 Implications

Three key points emerge from this portion of the analysis. This set of analyses aims to identify a point for each metric that would be discriminately valid. I did this by examining the relationship between longitudinal teacher attrition and student outcomes to determine a point of atypicality. It is this point of atypicality that serves as a threshold for the proposed metrics. The key findings of these analyses are well aligned with this aim.

First, while higher rates of 1- to 4-year average attrition are associated with negative student outcomes compared to schools experiencing less attrition, those relationships do not appear to be strictly linear. The consistent identification of an inverted U shape with an

[15] The original preferred model predicting ELA achievement from 2-year average attrition is only approaching statistically significance.

especially prominent drop off on the high end of attrition rates suggests these associations appear to be driven by relatively extremely high attrition rates associated with significant reductions in student achievement. Thus, it appears that while there may be some variation amongst schools experiencing relatively low and moderate teacher attrition, and while students with more direct exposure to attrition at the grade and classroom level may experience adverse effects, when considering school level attrition at the aggregate only the most extreme cases appear to be associated with the predicted negative outcomes.

Second, the consistent predictive power of 3-year average attrition rates suggests this measure is a valid indicator of chronic attrition. Furthermore, the observed inflection point of this measure at or above 30% and multiyear average rates appears to be a critical turning point for associated student outcomes. Contrary to my initial hypothesis, this study does not identify multiple inflection points; instead, a single inflection point is worth additional examination. That said, experiencing 30% average attrition over three years is very uncommon for schools, so the most severe harms are concentrated in a small subset of schools.

Furthermore, while I initially sought to define multiple attrition constructs (episodic, chronic, and cumulative attrition), the data examined does not justify the distinctiveness of these constructs in practice. Instead, the high level of overlap between the outcomes predicted by the 1-, 2-, and 3-year average attrition rate models suggests that while 3-year average attrition rates emerge as the most reliable indicator, shorter-term measures may yet offer some insight into emerging patterns of instability.

Ultimately, building on analyses conducted in Chapter 4, these analyses support the assumption that some patterns of teacher attrition are associated with more acute harm to students and that it is possible to establish a threshold of atypicality. In this case, evidence suggests that chronic attrition is associated with harm to students when the average attrition rate exceeds 30% over three years.

Chapter 6: Conclusion

This dissertation set out to develop data-informed measures of three longitudinal teacher attrition constructs, episodic, chronic, and cumulative attrition, based on the association between each measure and associated student outcomes. Using an argument-based validity framework, I sought to develop data-informed measures of attrition that could inform policy and practice meaningfully. Through a combination of empirical analysis and theoretical refinement, this work has contributed to the field by offering new insights into how specific attrition thresholds and patterns manifest in different school environments and how these, in turn, affect student outcomes.

As I conclude this dissertation, I consider the implications of these findings for educational policy and how they can guide future research on teacher attrition. In this concluding chapter, I summarize the major contributions of this research, discuss the policy relevance of the proposed benchmarks, and suggest avenues for future investigation in this evolving field.

Contributions to the Field

This dissertation makes three important contributions to the field. First, and perhaps most significantly, it establishes a simple, appropriate, and actionable metric for chronic attrition, which can inform future policy interventions. Second, it suggests that linear modeling alone may not be sufficient to accurately capture the relationship between longitudinal forms of teacher attrition and student outcomes. Finally, it underscores the need for a systematic data-driven process to establish meaningful and policy measures.

This dissertation makes a substantive contribution to both the research and policy spheres by establishing a simple policy-relevant metric for chronic attrition. While much of the previous literature focuses on continuous 1-year attrition rates, this study probes and validates specific thresholds for identifying when chronic attrition becomes particularly harmful to students. For example, this study concludes that chronic attrition, defined as turnover rates that exceed 30% over multiple years, is linked to even more severe negative outcomes. These findings emphasize the importance of prioritizing schools experiencing these acute chronic patterns over more general approaches to addressing turnover. Furthermore, rather than noting an overall trend, this analysis provides a straightforward way to differentiate between schools with typical and generally unharmful levels of attrition and those experiencing destabilizing turnover. This straightforward yet nuanced understanding can lead to more targeted interventions, helping districts prioritize resources where they are needed most.

Additionally, these benchmarks are also set at a relatively high threshold, suggesting that only a subset of schools experience these concerning patterns. If we used these benchmarks to identify schools in the greatest need of intervention or support across 1,397 schools in my sample, it would have identified 149, or 10.67%, of schools as experiencing high chronic attrition for at least one year in the 11-year period between 2009 and 2019. While the number of schools identified is not insignificant, these metrics provide a manageable and targeted approach for policymakers to focus interventions on the most at-risk schools, ensuring that resources are directed where they will have the greatest impact.

Building off the establishment of this actionable benchmark is the finding that linear modeling alone may not be sufficient to capture the full relationship between longitudinal teacher attrition and student outcomes. Much of the prior research on teacher attrition assumes a linear relationship, where increasing attrition is expected to lead to a proportional decline in student outcomes. However, the analyses in this dissertation show that the association between teacher attrition and student outcomes is more complex and often nonlinear, particularly when considering multiyear attrition patterns. By incorporating quadratic terms into the models, this study reveals critical turning points where the negative impacts of attrition accelerate. This nonlinearity aligns with organizational theory and suggests that schools may be able to absorb some level of teacher turnover without significant risk to student outcomes, but that past a certain point, the association becomes much more severe (Dalton & Todor, 1979; Wallace & Gaylor, 2012). While this modeling approach does not necessarily affect the overall trend we might expect to observe—that higher rates are related to more negative outcomes—it does suggest that this relationship is more complex and suggests that not all increases in teacher attrition are necessarily cause for concern. In particular, this study emphasizes that only a small percentage of schools with extremely high teacher attrition rates may be driving these negative patterns. In most cases, schools appear to be able to withstand a considerable amount of school-level teacher attrition before they are associated with harmful student outcomes.

Finally, this dissertation demonstrates the value of the argument-based validity approach to the generation of measures. This approach requires a rigorous examination of the assumptions underlying each construct, ensuring that the measures used are not only theoretically sound but also empirically justified. Based on past research (Holme et al., 2017), I began this investigation assuming that schools could experience at least three distinct patterns of attrition: episodic, chronic, and cumulative. The argument-based validity framework, however, mandates that researchers critically interrogate the logic and empirical evidence supporting these distinctions. Through this process, it became clear that, while chronic and cumulative attrition may appear theoretically distinct, they overlap significantly in practice. The high level of empirical overlap suggests that investigating these as separate constructs is not warranted, as schools experiencing high chronic attrition tend to experience high rates of cumulative attrition as well. Furthermore, the lack of distinct patterns between 1-year school-level attrition rates and longer-term measures does not support the establishment of episodic attrition as a meaningful or separate construct. This finding exemplifies the strength of the argument-based validity approach, as it pushes researchers to refine assumptions, leading to more accurate and practically meaningful measures. This ensures that the resulting metrics better reflect authentic phenomena, making these metrics more reliable for both research and policy applications.

Additionally, throughout this analysis, I was pushed to justify and re-evaluate assumptions to generate measures that provide validity for use within this study or that make sense from an analytic or research perspective, as well as measures that offer practical utility to policymakers and practitioners. In the same way argument-based validity prompts re-examination of existing measures, researchers can use this same process to be more thoughtful and deliberate in developing new measures in a data-informed way that centers the measures' intended use at the forefront.

Policy Implications

In addition to contributing to the research community, this study offers three important policy implications. First, this study suggests that there are thresholds above and below which attrition is and is not associated with harm to students. Schools, districts, and states can also use these thresholds to prioritize environments needing support or intervention. Furthermore, it offers motivation to correct our current rhetoric about the urgency of addressing widespread teacher shortages. Second, the strong overlap between chronic and cumulative attrition suggests that most long-term problems are likely associated with more systematic school-level factors. Finally, this study documents how consistent teacher losses over multiple years are associated with harms to students; this motivates the need for district leaders to consider the development of data systems that allow them to monitor this form of year-over-year attrition in order to be prepared to respond appropriately.

This dissertation's biggest contribution to policy and practice is offering more precise attrition constructs to measure and describe the attrition patterns occurring over time at the school level. While other scholars in the past have offered a range of considerations for possible metrics (Holme et al., 2017), these suggestions offer such a range of options that the options are almost too plentiful, leaving policymakers and practitioners little guidance on which trends are a priority to track. This study offers insight into those priorities using the data-informed argument-based validity approach. The models consistently identified average attrition of 30% or more over three years as a critical threshold for teacher attrition with associated negative student achievement outcomes. This finding suggests that policymakers should adopt the 30% 3-year average attrition rate as a critical point for flagging chronic attrition schools at risk of poor student outcomes. Policies to monitor and reduce teacher turnover should emphasize early intervention when attrition rates approach or exceed this level.

While past research continues to motivate to manage and mitigate the harms at the individual classroom or grade level (Henry & Redding, 2020; Ronfeldt et al., 2013; Sorensen & Ladd, 2020), this study suggests that only a small subset of schools are likely to produce sufficient instability to generate school-wide harms such that district and state resources should be focused on addressing chronic attrition in these select schools rather than implementing widespread blanket policies targeting all turnover. An analysis of the distribution of chronic attrition during this period reveals that 10 of the state's 24 school districts had at least one school experience chronic attrition between 2009 and 2019, with 8 of those districts having six or fewer schools fall into this category. Thus, while many of the schools are clustered in the larger school districts and are likely already on the radar of districts and states for other reasons, such as comprehensive support and intervention status, this attrition indicator offers an additional data point that can help sharpen the focus of support efforts. Rather than treating all turnover as equally problematic, chronic attrition can serve as a flag for deeper, sustained instability that may warrant targeted interventions. By incorporating this measure into existing school monitoring systems, districts and states can better differentiate between typical staffing challenges and more acute organizational strain—allowing them to allocate resources more strategically and equitably.

Furthermore, these patterns are experienced by just a few schools in multiple districts, and no schools in others. For many districts supporting and working with this subset of schools to identify and remedy root causes for these troubling patterns may be a manageable endeavor. Conversely, the absence of any schools experiencing chronic attrition in most school districts in the states further emphasizes the need to temper the broader rhetoric around teacher attrition. Instead of framing attrition as a universal crisis, policymakers and stakeholders should adopt a more nuanced perspective, focusing on chronic and high-level cases where intervention is most needed while recognizing that moderate turnover may not warrant alarm and can have neutral or positive effects in certain contexts.

Additionally, strong overlap between chronic and cumulative attrition patterns suggests that wider-scale attrition patterns drive both metrics. The overlap means that when schools experience relatively high attrition rates for multiple years, they are also highly likely to experience the loss of a large proportion of teachers over that period. Loss of a relatively small proportion of teachers over time might suggest a more localized problem within specific roles.

The combination of a sustained high rate of loss and a high percentage of teachers lost overtime suggests that the root causes of attrition are not confined to short-term disruptions or pockets of dysfunction but are embedded in the school's culture and operation. The overlap between chronic and cumulative attrition points to systematic problems because both forms of teacher turnover appear to be driven by persistent, underlying issues within schools rather than isolated or temporary events. Chronic attrition, which occurs over multiple years, and cumulative attrition, which reflects accumulated teacher turnover, are likely symptoms of broader structural problems within the school environment. While this analysis cannot inform the selection of what specific interventions would be most appropriate to address these troubling patterns within a school, these systematic patterns suggest a greater focus on broader retention as those schools struggle to retain any teacher across a period. In this case, focusing instead on addressing working conditions (Ingersoll, 2001) or offering targeted incentives (Clotfelter et al., 2008) may be more appropriate. While the specific circumstances and contextual features will need to be considered before selecting an intervention among those supported by other research, focusing on improving working conditions is a likely first step in addressing these problems.

Part of addressing this problem is setting the stage for improved teacher retention and creating data systems that are equipped to monitor these patterns over time at the school level. While many districts currently track overall teacher turnover rates on a school-by-school basis, these systems may not be designed to track nuances of longitudinal trends, such as sustained attrition over multiple years, patterns specific to grade levels, departments, or demographics, or the repeat exposure of students to new teachers over time. Given the associations documented in this analysis and the impacts on staff previously documented by other scholars (Sorensen & Ladd, 2020), evidence suggests these patterns are worthy of attention. Developing robust data systems will allow districts and schools to identify chronic attrition issues, detect early warning signs of instability, and evaluate the effectiveness of retention strategies. By leveraging these insights, schools can shift from reactive to proactive approaches, ensuring targeted interventions that address the root causes of attrition and fostering a more stable and supportive environment for both teachers and students.

Areas for Future Research

Three key areas emerge as worthy of additional research: exploring the effects of chronic attrition on additional student and staff outcomes, the situations and settings that may cause chronic attrition, and investigating policy interventions that are most effective at addressing these problems.

While this study focused on student achievement as the primary outcome of interest to inform metric development, there may be many other associated outcomes to consider. Sorenson and Ladd (2020) have already begun to examine the impacts this level of instability may have on teachers and other school features. These findings, combined with those outlined in this study, suggest that these patterns are likely to be associated with a wide range of school outcomes. In particular, attention to indicators of long-term student success can provide a more robust understanding of the consequences of attending schools dealing with chronic attrition.

In addition to continuing to examine the relationship between teacher attrition and other outcomes, it is vital to investigate how the accumulated exposure to instability manifests over multiple years. To isolate the impact of various durations of attrition patterns, this study only examined the attendance at each school type for a single year and the associated student outcomes. These estimates do not offer insight into how the accumulated effects of instability manifest in students exposed over multiple years. As students may spend multiple years attending a school struggling with chronic attrition, examining these accumulated harms is vital to understanding the true impacts of chronic attrition over a student's K-12 school career. Understanding these consequences will improve our motivation to address these issues.

Likewise, in addition to gaining more insight into the associated harms, future research should also attend to the situations and settings most likely to cause chronic attrition. While the existing literature provides insight into some common causes and correlates of 1-year attrition such as proportions of low-income and minoritized students (Allensworth et al., 2009; Guarino et al., 2011; Holme et al., 2017; Loeb et al., 2005), poor working conditions (Allensworth et al., 2009; Ingersoll, 2001), and lack of administrative support (Boyd et al., 2012; Grissom & Bartanen, 2018; Papay et al., 2017), it is crucial to identify the specific school contexts and environments that are most susceptible to chronic attrition. For instance, future research should explore whether schools in low-income areas, those with higher proportions of minority students, or those with high student–teacher ratios are more prone to experiencing sustained teacher turnover. Understanding the unique circumstances that make certain schools more vulnerable to chronic attrition will allow policymakers and educational leaders to tailor interventions to the needs of these schools.

Moreover, examining the role of leadership stability, community support, and teacher retention strategies in these settings could provide a clearer picture of what drives persistent turnover. This type of research would be invaluable for developing targeted policies that mitigate attrition and foster more stable, supportive environments that encourage teachers to stay long term, ultimately improving student outcomes in the process.

Given how long schools and districts have struggled with concerning patterns of teacher attrition, these problems are unlikely to be easily solved. However, I hope this dissertation can guide more nuanced conversations and target interventions in settings that pose the highest risk to students.

Appendix A

Characteristics of School Year Observations 2008–2019

	Total		Elementary		Middle		High	
N		**15,976**	**65%**	**10,600**	**18%**	**2,958**	**15%**	**2,418**
	%	N	**%**	N	**%**	N	**%**	N
Urban	**22%**	3,515	**22%**	2,335	**19%**	557	**24%**	568
Suburban	**57%**	9,250	**58%**	6,161	**59%**	1,724	**51%**	1,217
Town	**5%**	729	**4%**	453	**5%**	160	**5%**	116
Rural	**17%**	2,673	**15%**	1,614	**17%**	495	**21%**	511
Small	**16%**	2,524	**18%**	1,873	**8%**	238	**7%**	168
Medium	**84%**	13,706	**82%**	8,727	**92%**	2,720	**93%**	2,250
Principal new to role	**18%**	2,593	**16%**	1,584	**22%**	583	**18%**	391
STUDENT FEATURES	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD
% minoritized students	**53%**	34%	**53%**	31%	**53%**	43%	**53%**	33%
Female	**47%**	7%	**46%**	5%	**49%**	9%	**50%**	7%
EL	**4%**	9%	**6%**	11%	**2%**	5%	**2%**	6%
FARMS	**46%**	33%	**45%**	29%	**43%**	50%	**37%**	23%
SWD	**10%**	14%	**9%**	9%	**10%**	10%	**8%**	10%
%Proficient plus ELA	**34%**	22%	**32%**	16%	**60%**	28%	**16%**	7%
%Proficient plus math	**30%**	22%	**30%**	17%	**51%**	28%	**8%**	5%
Attendance	**10.5**	6.00	**9.02**	2.70	**10.73**	6.80	**15.16**	10.13
TEACHERS	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD
Teachers per school	**45.7**	25.4	**35.5**	12.2	**52.7**	17.1	**84.2**	35.5
Teacher % non-white	**26%**	26%	**26%**	26%	**27%**	25%	**29%**	27%
Alt licensure	**1%**	4%	**1%**	4%	**2%**	4%	**2%**	4%
Conditional certification rate	**2%**	5%	**2%**	5%	**3%**	5%	**4%**	6%
Out-of-state prepared	**16%**	10%	**15%**	10%	**17%**	10%	**20%**	10%
Novice teacher	**12%**	9%	**12%**	10%	**13%**	11%	**10%**	8%
MA teacher	**54%**	15%	**52%**	16%	**55%**	14%	**58%**	13%
Student–teacher ratio	**13.7**	2.83	**13.9**	2.44	**13.1**	2.74	**14.3**	2.89

APPENDIX B

Student Sample Characteristics — 6th Graders in 2017–2019

	Total		**2016**		**2017**		**2018**		**2019**	
N	108,863						53,655		55,208	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Achievement ELA	0.10	0.99	0.11	0.98	0.11	0.98	0.09	0.99	0.09	0.99
Achievement math	0.07	0.99	0.07	0.98	0.07	0.99	0.06	0.99	0.06	0.99
Attendance	8.99	9.43	8.09	8.60	8.90	9.24	9.40	9.85	9.50	9.85
Previous achievement ELA	0.09	0.99	0.09	0.99	0.10	0.98	0.09	0.99	0.08	0.99
Previous achievement math	0.08	0.98	0.09	0.98	0.09	0.98	0.08	0.99	0.07	0.98
Previous attendance	8.27	7.58	7.81	7.14	7.67	7.14	8.61	7.85	8.91	8.04
	%	N	%	N	%	N	%	N	%	N
EL	4%	8,533	3%	1,513	3%	1,740	4%	2,331	5%	2,949
FARMs	40%	86,289	40%	20,579	40%	20,674	41%	22,512	40%	22,524
SWD	17%	35,216	16%	8,329	16%	8,502	17%	8,974	17%	9,411
Girls	49%	104,447	49%	25,164	49%	25,510	49%	26,451	49%	27,322
Asian	7%	15,886	7%	3,800	8%	3,974	7%	3,993	7%	4,119
Black/AA	29%	60,946	28%	14,343	28%	14,623	29%	15,764	29%	16,216
Hispanic	16%	33,262	14%	7,024	15%	7,701	16%	8,826	17%	9,711
White	43%	91,578	46%	23,373	44%	22,814	42%	22,705	41%	22,686
Other	5%	11,376	5%	2,696	5%	2,699	5%	2,926	5%	3,055

School Level Averages for Middle Schools 2017–2019

	Total		**2016**		**2017**		**2018**		**2019**	
	N	930	231		233		233		233	
	%	N	**%**	N	**%**	N	**%**	N	**%**	N
Urban	19%	180	20%	46	20%	47	19%	44	18%	43
Suburban	61%	571	61%	141	61%	141	62%	144	62%	145
Town	4%	40	4%	10	4%	10	4%	10	4%	10
Rural	15%	139	15%	34	15%	35	15%	35	15%	35
Small	4%	41	5%	12	5%	11	3%	8	4%	10
Medium	96%	890	95%	220	95%	222	97%	225	96%	223
Principal new to role	23%	212	22%	50	26%	59	25%	57	20%	46
TEACHER POPULATION	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD
Teachers per school	56.4	17.5	54.0	16.7	54.2	17.6	55.8	17.5	56.4	17.5
Teacher % non-white	26%	25%	25%	24%	26%	24%	27%	25%	28%	26%
Alt licensure	1%	4%	1%	4%	1%	4%	1%	3%	1%	4%
Conditional certification rate	3%	5%	2%	3%	3%	4%	3%	5%	5%	6%
Out-of-state prepared	12%	7%	14%	8%	12%	7%	12%	6%	11%	6%
Novice teacher	12%	9%	13%	10%	11%	8%	11%	9%	11%	9%
MA teacher	59%	14%	59%	14%	59%	15%	59%	13%	59%	14%
Student–teacher ratio	13.6	2.3	13.6	2.4	13.7	2.2	13.7	2.1	13.7	2.3

	Total		2016		2017		2018		2019	
	N 930		231		233		233		233	
STUDENT POPULATION	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD	**Mean**	SD
Proficient + ELA	40%	19%	37%	18%	39%	18%	41%	18%	43%	20%
Proficient + math	32%	19%	32%	19%	32%	19%	34%	20%	32%	20%
EL	5%	7%	4%	6%	4%	7%	5%	7%	6%	8%
FARMs	44%	24%	45%	25%	44%	24%	44%	23%	43%	25%
SWD	5%	7%	4%	6%	4%	7%	5%	7%	6%	8%
Girls	18%	10%	18%	9%	18%	10%	17%	8%	18%	12%
Asian	48%	8%	48%	8%	49%	8%	48%	8%	48%	8%
Black/AA	6%	8%	6%	8%	7%	9%	6%	9%	6%	9%
Hispanic	32%	29%	32%	30%	33%	29%	32%	28%	32%	28%
White	41%	30%	43%	31%	41%	30%	40%	30%	40%	30%
Other	41%	30%	43%	31%	41%	30%	40%	30%	40%	30%

* Values have an *n* count of less than ten cannot be reported due to data suppression rules

**Values suppressed due to secondary suppression rules

APPENDIX C: Points of Comparison from Prior Research

Source	Comparison	Results
Ronfeldt, Loeb, Wycoff (2013)	1-year grade-level teacher attrition – The difference between students in grades with 0% vs. 100% attrition	Math –.086 (.011) ELA –.049 (.010)
Sorensen and Ladd (2020)	3-year subject teacher turnover – The difference between students in grades with 0% vs. 100% attrition in each subject	Math –.134 (.028) ELA –.072 (.023)
Henry and Redding (2018)	1-year within-year grade-level turnover elementary – The difference between students in grades with 0% vs. 100% attrition 1-year within-year grade-level turnover middle school – The difference between students in grades with 0% vs. 100% attrition	Math –.069 (.010) ELA –.051 (.010) Math –.106 (.010) ELA –.042 (.012)

APPENDIX D

Model Comparison 1-Year Attrition Rate

	Predicting math achievement				Predicting ELA achievement			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Linear	Quadratic term	Cubic term	Natural log term	Linear	Quadratic term	Cubic term	Natural log term
1-year attrition rate	–0.0429	0.371***	0.583**		–0.00469	0.236	0.492	
	(0.0628)	(0.144)	(0.274)		(0.0689)	(0.158)	(0.302)	
1-year attrition rate (x^2)		–1.004***	–1.983*			–0.582*	–1.764	
		(0.315)	(1.125)			(0.344)	(1.237)	
1-year attrition rate (x^3)			1.173				1.410	
			(1.293)				(1.418)	
1-year attrition rate (ln(x))				–0.0103				0.000240
				(0.00815)				(0.00896)
Constant	0.174***	0.137***	0.127***	0.147***	–0.0125	–0.0336	–0.0466	–0.0127
	(0.0388)	(0.0402)	(0.0419)	(0.0410)	(0.0426)	(0.0444)	(0.0462)	(0.0451)
Observations	206,196	206,196	206,196	206,196	206,318	206,318	206,318	206,318
Number of groups	915	915	915	915	914	914	914	914

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Model Comparison 2-Year Average Attrition Rate

	Predicting math achievement				Predicting ELA achievement			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Linear	Quadratic term	Cubic term	Natural log term	Linear	Quadratic term	Cubic term	Natural log term
2-year average attrition rate	−0.155*	0.755***	0.599		0.0324	0.481*	0.254	
	(0.0869)	(0.248)	(0.544)		(0.0954)	(0.273)	(0.600)	
2-year average attrition rate (x^2)		−2.457***	−1.564			−1.209*	0.0814	
		(0.628)	(2.832)			(0.690)	(3.112)	
2-year average attrition rate (x^3)			−1.467				−2.115	
			(4.540)				(4.974)	
2-year average attrition rate (ln(x))				−0.0135				−0.000620
				(0.0118)				(0.0129)
Constant	0.190***	0.118***	0.126**	0.139***	−0.0212	−0.0565	−0.0459	−0.0176
	(0.0400)	(0.0437)	(0.0492)	(0.0449)	(0.0439)	(0.0483)	(0.0543)	(0.0493)
Observations	205,151	205,151	205,151	205,151	205,275	205,275	205,275	205,275
Number of groups	909	909	909	909	908	908	908	908

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Model Comparison 3-Year Average Attrition Rate

	Predicting math achievement				Predicting ELA achievement			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Linear	Quadratic term	Cubic term	Natural log term	Linear	Quadratic term	Cubic term	Natural log term
3-year average attrition rate	−0.199**	0.726**	−0.383		0.0502	0.832**	−0.412	
	(0.0987)	(0.301)	(0.710)		(0.108)	(0.330)	(0.776)	
3-year average attrition rate (x^2)		−2.469***	3.903			−2.083**	5.041	
		(0.760)	(3.772)			(0.833)	(4.112)	
3-year average attrition rate (x^3)			−10.76*				−11.99*	
			(6.237)				(6.779)	
3-year average attrition rate (ln(x))				−0.0121				0.0200
				(0.0143)				(0.0156)
Constant	0.192***	0.118**	0.170***	0.139***	−0.0244	−0.0866*	−0.0280	0.0235
	(0.0402)	(0.0459)	(0.0550)	(0.0478)	(0.0441)	(0.0505)	(0.0604)	(0.0523)
Observations	204,360	204,360	204,360	204,360	204,501	204,501	204,501	204,501
Number of groups	903	903	903	903	902	902	902	902

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Model Comparison 4-Year Attrition Rate

	Predicting math achievement				Predicting ELA achievement			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	Linear	Quadratic term	Cubic term	Natural log term	Linear	Quadratic term	Cubic term	Natural log term
4-year average attrition rate	–0.235**	0.652**	–0.937		0.0631	0.686*	–1.356	
	(0.107)	(0.332)	(0.806)		(0.118)	(0.366)	(0.884)	
4-year average attrition rate (x^2)		–2.336***	6.650			–1.638*	9.882**	
		(0.829)	(4.239)			(0.911)	(4.635)	
4-year average attrition rate (x^3)			–15.07**				–19.26**	
			(6.971)				(7.599)	
4-year average attrition rate (ln(x))				–0.0214				0.0148
				(0.0164)				(0.0180)
Constant	0.192***	0.122***	0.197***	0.115**	–0.0272	–0.0762	0.0197	0.0127
	(0.0402)	(0.0471)	(0.0583)	(0.0513)	(0.0442)	(0.0519)	(0.0641)	(0.0565)
Observations	203,775	203,775	203,775	203,775	203,916	203,916	203,916	203,916
R-squared	899	899	899	899	898	898	898	898

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX E
School-Wide Teacher Attrition Regression Models Predicting Math Achievement

VARIABLES	1-year attrition	2-year avg attrition	3-year avg attrition	4-year avg attrition
Attrition predictor	0.583**	0.755***	0.726**	0.652**
	(0.274)	(0.248)	(0.301)	(0.332)
Attrition predictor (x^2)	–1.983*	–2.457***	–2.469***	–2.336***
	(1.125)	(0.628)	(0.760)	(0.829)
Prior year math achievement	0.605***	0.606***	0.606***	0.606***
	(0.00174)	(0.00175)	(0.00175)	(0.00175)
Prior year ELA achievement	0.221***	0.221***	0.221***	0.221***
	(0.00175)	(0.00176)	(0.00176)	(0.00176)
Prior year attendance	–0.00235***	–0.00234***	–0.00235***	–0.00235***
	(0.000147)	(0.000147)	(0.000148)	(0.000148)
EL	–0.0397***	–0.0399***	–0.0399***	–0.0402***
	(0.00622)	(0.00623)	(0.00624)	(0.00625)
FARMSs	–0.0686***	–0.0686***	–0.0685***	–0.0683***
	(0.00257)	(0.00258)	(0.00258)	(0.00259)
SWD	–0.0781***	–0.0777***	–0.0779***	–0.0776***
	(0.00301)	(0.00302)	(0.00302)	(0.00303)
Female	–0.0388***	–0.0386***	–0.0386***	–0.0386***
	(0.00213)	(0.00213)	(0.00214)	(0.00214)
Black students	–0.112***	–0.112***	–0.112***	–0.112***
	(0.00326)	(0.00327)	(0.00327)	(0.00328)
Asian students	0.0969***	0.0973***	0.0971***	0.0973***
	(0.00440)	(0.00442)	(0.00443)	(0.00444)
Hispanic students	–0.0627***	–0.0623***	–0.0624***	–0.0624***
	(0.00374)	(0.00375)	(0.00376)	(0.00376)
Another race/ethnicity	–0.0334***	–0.0332***	–0.0332***	–0.0334***
	(0.00477)	(0.00478)	(0.00479)	(0.00479)
Urban schools	–0.0115	–0.0129	–0.0128	–0.0132
	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Rural schools	0.00676	0.00589	0.00487	0.00576
	(0.0141)	(0.0141)	(0.0143)	(0.0143)
Town schools	0.0327	0.0316	0.0300	0.0279
	(0.0228)	(0.0228)	(0.0228)	(0.0227)
% Novice teachers	–0.0770	–0.0277	–0.0239	–0.0717
	(0.0768)	(0.0812)	(0.0790)	(0.0787)
% Teachers w/ masters+	0.0143	0.0256	0.0201	0.0156
	(0.0535)	(0.0539)	(0.0544)	(0.0543)
% Teachers in high-attrition subject	0.0260	0.0292	0.0361	0.0555
	(0.0699)	(0.0708)	(0.0718)	(0.0720)

VARIABLES	1-year attrition	2-year avg attrition	3-year avg attrition	4-year avg attrition
% Teachers Non-White	–0.216***	–0.208***	–0.206***	–0.208***
	(0.0498)	(0.0501)	(0.0505)	(0.0508)
% Teachers out-of-state trained	–0.0239	–0.0258	–0.0352	–0.0397
	(0.0748)	(0.0752)	(0.0761)	(0.0767)
% Teachers alternatively certified	–0.464***	–0.495***	–0.440**	–0.456**
	(0.172)	(0.175)	(0.185)	(0.185)
% Teachers w/ conditionally certified	0.0639	0.106	0.108	0.118
	(0.115)	(0.115)	(0.117)	(0.118)
Principal in first year	–5.46e-05	–0.000742	0.000771	–0.000834
	(0.00883)	(0.00880)	(0.00883)	(0.00883)
Middle/high school	0.000490	0.00424	–0.000493	–0.00745
	(0.0212)	(0.0216)	(0.0223)	(0.0229)
Large schools	0.0617**	0.0517*	0.0638**	0.0599*
	(0.0297)	(0.0300)	(0.0307)	(0.0307)
Student–teacher ratio	–0.00220	–0.00192	–0.00116	–0.00175
	(0.00309)	(0.00315)	(0.00320)	(0.00323)
% ELs	0.464***	0.467***	0.444***	0.451***
	(0.116)	(0.116)	(0.117)	(0.117)
% FARMs	0.0730	0.0822*	0.0926*	0.106**
	(0.0473)	(0.0474)	(0.0478)	(0.0479)
% SWD	0.253***	0.280***	0.289***	0.279***
	(0.0921)	(0.0922)	(0.0947)	(0.0948)
% Female	–0.0138	–0.00855	–0.0168	0.00129
	(0.0623)	(0.0641)	(0.0664)	(0.0665)
% Black	0.303***	0.300***	0.298***	0.298***
	(0.0398)	(0.0399)	(0.0404)	(0.0406)
% Asian	–0.0884	–0.0842	–0.0915	–0.0781
	(0.0766)	(0.0777)	(0.0785)	(0.0785)
% Hispanic	0.104	0.0874	0.0915	0.0815
	(0.0712)	(0.0714)	(0.0718)	(0.0718)
% Another race/ethnicity	–0.372**	–0.405**	–0.424**	–0.444***
	(0.168)	(0.169)	(0.170)	(0.171)
% Proficient + ELA	–0.0855	–0.102	–0.113	–0.107
	(0.0776)	(0.0777)	(0.0782)	(0.0781)
% Proficient + math	0.940***	0.948***	0.965***	0.954***
	(0.0839)	(0.0844)	(0.0853)	(0.0856)
Constant	0.127***	0.118***	0.118**	0.122***
	(0.0419)	(0.0437)	(0.0459)	(0.0471)
Observations	206,196	205,151	204,360	203,775
number of groups	915	909	903	899

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX E
School-Wide Teacher Attrition Regression Models Predicting ELA Achievement

VARIABLES	1-year attrition	2-year avg attrition	3-year avg attrition	4-year avg attrition
Attrition predictor	0.236	0.481*	0.832**	0.686*
	(0.158)	(0.273)	(0.330)	(0.366)
Attrition predictor (x^2)	–0.582*	–1.209*	–2.083**	–1.638*
	(0.344)	(0.690)	(0.833)	(0.911)
Prior year math achievement	0.219***	0.219***	0.219***	0.219***
	(0.00186)	(0.00186)	(0.00187)	(0.00187)
Prior year ELA achievement	0.584***	0.585***	0.584***	0.584***
	(0.00187)	(0.00187)	(0.00188)	(0.00188)
Prior year attendance	–0.00104***	–0.00103***	–0.00104***	–0.00105***
	(0.000156)	(0.000157)	(0.000157)	(0.000157)
EL	–0.0966***	–0.0964***	–0.0964***	–0.0964***
	(0.00664)	(0.00665)	(0.00666)	(0.00666)
FARMSs	–0.0865***	–0.0865***	–0.0866***	–0.0868***
	(0.00274)	(0.00275)	(0.00275)	(0.00276)
SWD	–0.135***	–0.135***	–0.135***	–0.135***
	(0.00321)	(0.00322)	(0.00322)	(0.00323)
Female	0.173***	0.173***	0.173***	0.173***
	(0.00227)	(0.00227)	(0.00228)	(0.00228)
Black students	–0.0551***	–0.0553***	–0.0556***	–0.0555***
	(0.00347)	(0.00348)	(0.00349)	(0.00349)
Asian students	0.0675***	0.0670***	0.0677***	0.0680***
	(0.00469)	(0.00471)	(0.00472)	(0.00473)
Hispanic students	–0.0323***	–0.0323***	–0.0326***	–0.0324***
	(0.00398)	(0.00399)	(0.00400)	(0.00400)
Another race/ethnicity	–0.0125**	–0.0126**	–0.0127**	–0.0132***
	(0.00508)	(0.00510)	(0.00510)	(0.00511)
Urban schools	–0.0319**	–0.0329**	–0.0325**	–0.0329**
	(0.0146)	(0.0146)	(0.0146)	(0.0146)
Rural schools	0.00769	0.00721	0.00738	0.00594
	(0.0155)	(0.0156)	(0.0157)	(0.0158)
Town schools	–0.0462*	–0.0461*	–0.0438*	–0.0449*
	(0.0251)	(0.0252)	(0.0251)	(0.0251)
% Novice teachers	–0.113	–0.164*	–0.136	–0.147*
	(0.0845)	(0.0897)	(0.0869)	(0.0869)
% Teachers w/ masters+	–0.0144	–0.0150	–0.0108	–0.0159
	(0.0590)	(0.0596)	(0.0599)	(0.0600)
% Teachers in high-attrition subject	0.0566	0.0721	0.0547	0.0554
	(0.0771)	(0.0783)	(0.0790)	(0.0794)

VARIABLES	1-year attrition	2-year avg attrition	3-year avg attrition	4-year avg attrition
% Teachers Non-White	–0.103*	–0.0883	–0.0859	–0.104*
	(0.0549)	(0.0553)	(0.0556)	(0.0561)
% Teachers out-of-state trained	0.0819	0.0888	0.0984	0.0954
	(0.0826)	(0.0832)	(0.0838)	(0.0847)
% Teachers alternatively certified	–0.00616	–0.0259	0.0386	–0.0161
	(0.189)	(0.192)	(0.203)	(0.204)
% Teachers w/ conditionally certified	0.0624	0.0640	0.0456	0.0589
	(0.126)	(0.127)	(0.129)	(0.130)
Principal in first year	0.00149	0.00143	0.00324	0.00342
	(0.00972)	(0.00973)	(0.00972)	(0.00975)
Middle/high school	–0.0533**	–0.0562**	–0.0579**	–0.0497**
	(0.0233)	(0.0238)	(0.0245)	(0.0252)
Large schools	–0.00914	–0.0193	–0.00456	–0.00713
	(0.0326)	(0.0330)	(0.0336)	(0.0337)
Student–teacher ratio	–0.00225	–0.00367	–0.00289	–0.00293
	(0.00341)	(0.00348)	(0.00352)	(0.00357)
% ELs	0.488***	0.498***	0.457***	0.471***
	(0.128)	(0.129)	(0.129)	(0.129)
% FARMs	0.277***	0.281***	0.285***	0.291***
	(0.0521)	(0.0524)	(0.0525)	(0.0529)
% SWD	0.687***	0.691***	0.730***	0.719***
	(0.101)	(0.101)	(0.104)	(0.104)
% Female	–0.0945	–0.0829	–0.108	–0.0971
	(0.0684)	(0.0707)	(0.0730)	(0.0733)
% Black	0.148***	0.138***	0.132***	0.142***
	(0.0439)	(0.0441)	(0.0444)	(0.0448)
% Asian	–0.0148	–0.0125	–0.00792	–0.00987
	(0.0845)	(0.0859)	(0.0864)	(0.0866)
% Hispanic	–0.0529	–0.0650	–0.0558	–0.0585
	(0.0785)	(0.0789)	(0.0790)	(0.0793)
% Another race/ethnicity	–0.640***	–0.667***	–0.694***	–0.698***
	(0.185)	(0.186)	(0.186)	(0.188)
% Proficient + ELA	1.672***	1.675***	1.668***	1.669***
	(0.0855)	(0.0858)	(0.0860)	(0.0862)
% Proficient + math	–0.654***	–0.653***	–0.632***	–0.624***
	(0.0926)	(0.0933)	(0.0939)	(0.0945)
Constant	–0.0336	–0.0565	–0.0866*	–0.0762
	(0.0444)	(0.0483)	(0.0505)	(0.0519)
Observations	206,318	205,275	204,501	203,916
R-squared	914	908	902	898

Model includes school-year random effects. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX F: Standard Deviation Thresholds by Attrition Measure

	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD
1-year attrition	0.86%	8.21%	15.57%	22.92%	30.27%	37.63%	44.98%
2-year average attrition	2.94%	9.21%	15.49%	21.76%	28.03%	34.30%	40.57%
3-year average attrition	3.59%	9.49%	15.39%	21.29%	27.19%	33.09%	38.99%
4-year average attrition	3.74%	9.49%	15.25%	21.00%	26.75%	32.50%	38.25%

APPENDIX I: Predicted Margins: School-Wide Teacher Attrition Models

1-Year Attrition Raw

Attrition %	Predicting ELA 0%	10%	20%	30%	40%	50%	Predicting math 0%	10%	20%	30%	40%	50%
b	0.05	0.07	0.08	0.07	0.06	0.03	0.08	0.10	0.11	0.10	0.06	0.01
se	0.02	0.01	0.01	0.01	0.02	0.04	0.02	0.01	0.01	0.01	0.02	0.03
z	3.32	12.67	13.68	6.87	2.81	0.76	5.11	19.95	21.18	10.07	3.54	0.34
p-value	0.00	0.00	0.00	0.00	0.00	0.45	0.00	0.00	0.00	0.00	0.00	0.74
ll	0.02	0.06	0.07	0.05	0.02	–0.04	0.05	0.09	0.10	0.08	0.03	–0.05
ul	0.09	0.08	0.09	0.09	0.10	0.10	0.11	0.11	0.12	0.12	0.10	0.08

1-Year Attrition Standard Deviations

Attrition %	Predicting ELA 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD	Predicting math 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD
b	0.05	0.06	0.07	0.08	0.08	0.07	0.06	0.04	0.08	0.08	0.10	0.11	0.11	0.10	0.07	0.04
se	0.02	0.02	0.01	0.00	0.01	0.01	0.02	0.03	0.02	0.01	0.01	0.00	0.01	0.01	0.02	0.02
z	3.32	3.72	10.04	17.26	11.28	6.73	3.57	1.60	5.11	5.74	15.79	27.00	17.28	9.84	4.73	1.63
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10
ll	0.02	0.03	0.06	0.07	0.06	0.05	0.03	–0.01	0.05	0.05	0.09	0.10	0.10	0.08	0.04	-0.01
ul	0.09	0.09	0.08	0.09	0.09	0.09	0.10	0.10	0.11	0.11	0.11	0.12	0.12	0.12	0.10	0.09

2-Year Average Attrition Raw

Attrition %	Predicting ELA 0%	10%	20%	30%	40%	50%	Predicting math 0%	10%	20%	30%	40%	50%
b	0.03	0.07	0.08	0.07	0.03	–0.03	0.06	0.11	0.11	0.06	–0.03	–0.18
se	0.03	0.01	0.01	0.02	0.04	0.07	0.02	0.01	0.01	0.01	0.03	0.07
z	1.28	9.91	12.00	4.43	0.85	–0.40	2.43	17.13	18.00	4.43	–1.04	–2.72
p-value	0.20	0.00	0.00	0.00	0.39	0.69	0.01	0.00	0.00	0.00	0.30	0.01
ll	–0.02	0.05	0.07	0.04	–0.04	–0.17	0.01	0.09	0.10	0.03	–0.10	–0.31
ul	0.08	0.08	0.09	0.10	0.10	0.11	0.10	0.12	0.12	0.09	0.03	–0.05

2-Year Average Attrition Standard Deviations

Attrition %	Predicting ELA 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD	Predicting math 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD
b	0.03	0.05	0.07	0.08	0.08	0.07	0.06	0.03	0.06	0.08	0.10	0.11	0.10	0.07	0.03	–0.04
se	0.03	0.02	0.01	0.00	0.01	0.01	0.02	0.04	0.02	0.02	0.01	0.00	0.01	0.01	0.02	0.04
z	1.28	2.47	8.56	15.80	10.48	5.65	2.42	0.75	2.43	4.56	14.92	25.57	15.11	6.45	1.27	–1.19
p-value	0.20	0.01	0.00	0.00	0.00	0.00	0.02	0.46	0.01	0.00	0.00	0.00	0.00	0.00	0.20	0.23
ll	–0.02	0.01	0.05	0.07	0.07	0.05	0.01	–0.05	0.01	0.04	0.09	0.11	0.09	0.05	–0.01	–0.11
ul	0.08	0.08	0.08	0.09	0.09	0.10	0.10	0.10	0.10	0.11	0.12	0.12	0.12	0.10	0.07	0.03

3-Year Average Attrition

Attrition %	Predicting ELA 0%	10%	20%	30%	40%	50%	Predicting math 0%	10%	20%	30%	40%	50%
b	0.00	0.06	0.09	0.06	0.00	–0.10	0.06	0.11	0.11	0.06	–0.04	–0.19
se	0.03	0.01	0.01	0.02	0.04	0.09	0.03	0.01	0.01	0.02	0.04	0.08
z	0.07	8.41	11.57	3.67	0.03	–1.20	2.15	15.55	15.97	3.51	–1.13	–2.47
p-value	0.95	0.00	0.00	0.00	0.97	0.23	0.03	0.00	0.00	0.00	0.26	0.01
ll	–0.06	0.05	0.07	0.03	–0.08	–0.27	0.01	0.09	0.09	0.02	–0.12	–0.35
ul	0.06	0.08	0.10	0.10	0.09	0.07	0.11	0.12	0.12	0.09	0.03	–0.04

3-Year Average Attrition Standard Deviations

Attrition %	Predicting ELA 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD	Predicting math 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD
b	0.00	0.03	0.06	0.08	0.08	0.07	0.05	0.01	0.06	0.08	0.11	0.11	0.10	0.08	0.03	–0.03
se	0.03	0.02	0.01	0.01	0.01	0.01	0.02	0.04	0.03	0.02	0.01	0.00	0.01	0.01	0.02	0.04
z	0.07	1.43	7.44	16.06	10.38	5.53	2.09	0.24	2.15	4.48	14.07	24.82	13.88	6.16	1.41	–0.88
p-value	0.95	0.15	0.00	0.00	0.00	0.00	0.04	0.81	0.03	0.00	0.00	0.00	0.00	0.00	0.16	0.38
ll	–0.06	–0.01	0.05	0.07	0.07	0.05	0.00	–0.07	0.01	0.05	0.09	0.10	0.09	0.05	–0.01	–0.10
ul	0.06	0.07	0.08	0.09	0.10	0.10	0.10	0.09	0.11	0.12	0.12	0.12	0.12	0.10	0.07	0.04

4-Year Average Attrition

Attrition %	Predicting ELA 0%	10%	20%	30%	40%	50%	Predicting math 0%	10%	20%	30%	40%	50%
b	0.01	0.07	0.08	0.07	0.03	–0.05	0.07	0.11	0.10	0.05	–0.05	–0.19
se	0.03	0.01	0.01	0.02	0.05	0.09	0.03	0.01	0.01	0.02	0.04	0.08
z	0.38	7.99	10.55	3.77	0.54	–0.58	2.20	14.89	14.46	3.10	–1.07	–2.25
p-value	0.71	0.00	0.00	0.00	0.59	0.56	0.03	0.00	0.00	0.00	0.28	0.02
ll	–0.05	0.05	0.07	0.03	–0.07	–0.24	0.01	0.10	0.09	0.02	–0.13	–0.36
ul	0.08	0.08	0.10	0.11	0.12	0.13	0.13	0.12	0.12	0.09	0.04	–0.02

4-Year Average Attrition Standard Deviations

Attrition %	Predicting ELA 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD	Predicting math 0	–2 SD	–1 SD	Mean	1 SD	2 SD	3 SD	4 SD
b	0.01	0.04	0.06	0.08	0.08	0.08	0.06	0.04	0.07	0.09	0.11	0.11	0.10	0.08	0.03	–0.02
se	0.03	0.02	0.01	0.01	0.01	0.01	0.02	0.04	0.03	0.02	0.01	0.00	0.01	0.01	0.02	0.04
z	0.38	1.64	7.06	15.58	9.71	5.64	2.62	0.89	2.20	4.44	13.42	24.47	12.89	5.90	1.52	–0.67
p-value	0.71	0.10	0.00	0.00	0.00	0.00	0.01	0.38	0.03	0.00	0.00	0.00	0.00	0.00	0.13	0.50
ll	–0.05	–0.01	0.05	0.07	0.07	0.05	0.02	–0.04	0.01	0.05	0.09	0.10	0.09	0.05	–0.01	–0.10
ul	0.08	0.08	0.08	0.09	0.10	0.11	0.11	0.11	0.13	0.13	0.12	0.12	0.12	0.10	0.08	0.05

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